TESTING THE VALIDITY OF THE CAPITAL ASSET PRICING MODEL DURING THE COVID-19 PANDEMIC:

A comparison between pre-pandemic and pandemic periods

Aarne Airinen

International Business
Bachelor's Thesis
Supervisor: Roman Stepanov
Date of approval: 9 April 2021

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AALTO UNIVERSITY SCHOOL OF BUSINESS Mikkeli Campus	ABSTRACT OF BACHELOR'S THESIS

Author: Aarne Airinen

Title of thesis: Testing the validity of the Capital Asset Pricing Model during the Covid-19 pandemic: A comparison between pre-pandemic and pandemic periods

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Supervisor: Roman Stepanov

Objectives

The main objective of the study is to test the validity of the CAPM during the Covid-19 pandemic by exploring the significance of the difference between returns of low and high beta stocks in five indices. In addition, the study aims to provide investors with knowledge of the model in order to help them value investments in an efficient manner. Furthermore, the study aims to add a contribution to the study of the validity CAPM, and the relationship between risk and returns, by testing the model under unusual market conditions.

Summary

To achieve the objectives of the study, the author collected daily, weekly, and monthly stock and index prices in order to calculate estimated returns and beta values. Based on the calculated betas, the stocks were divided into high and low beta stocks. The two groups were compared through a two-tailed t-test that highlighted the significance of the difference between the returns of the two groups of stocks.

Conclusions

The results of the t-test analysis were unable to reject the null hypothesis, that there is a significant difference between the returns of low and high beta stocks, during the Covid-19 pandemic. As such, it can be concluded that the CAPM is not valid in the five selected indices, during the Covid-19 pandemic. The findings further support the pre-existing notion that the CAPM is not valid in developed markets.

Key words: finance, stock markets, s&p 100, dax, ftse 100, omx helsinki 25, nikkei 225, capm, capital asset pricing model, beta, covid-19, systematic risk, rate of return.
Language: English

Grade:

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1. INTRODUCTION

This thesis will begin by providing the background for the study, as well as a description of the research problem. Following these two sections, the author will explain the chosen research questions, that will be used to solve the research problem. Finally, the main objectives of the research will be given, as well as a guide to the structure of the study, in order to help the reader follow the research paper.

1.1 Background

The stock market, which has evolved into a driving force of the global economy, is a central part of the financial system. In its core, lies the issue of security pricing. More specifically, the issue of risk versus reward, arises. Securities that hold a higher degree of risk should come with a higher level of returns to entice the investor. However, determining how much excess return a higher level of risk should provide, is not so clear. To help the investor determine how much they should expect to gain in returns based on a certain level of risk, asset pricing models have been created. The most notable of the group, is the Capital Asset Pricing Model (CAPM). It was one of the earliest asset pricing models that allowed investors to estimate returns based on risk, while also building upon the ideas of an efficient portfolio. Ever since its first introduction, the CAPM has remained widely popular, and is still often taught as the first entry into the field of asset pricing.

Despite its longstanding fame, now reaching almost six decades, the CAPM has also received its share of criticism. The model proposes a simple linear positive relationship between risk and return, meaning that as risks increase, so should the expected returns. This point has been heavily scrutinised, with results both for, and against, emerging. Although plenty of studies about the validity of the CAPM have been conducted, findings remain unclear, as time periods, as well as market locations, provide varying results. Since there is no clear answer to whether the model is valid, there is room to examine it under new and uncommon market conditions, in an effort to increase the understanding of how, and when, the model might work. This information would prove valuable for both the average investor, as well as the professional one, as it would help in applying the CAPM when it is at its most useful.

In an effort to increase the amount of literature on the validity of the Capital Asset Pricing Model, the author will examine the model and its validity under the market conditions brought along by the Covid-19 pandemic. More specifically, the study will examine the 20 largest companies in the S&P 100, DAX, FTSE 100, OMX Helsinki 25, and Nikkei 225, in two periods. The first period, which acts as the control, is between March 1st, 2019 and December 31st, 2019, as it represents a period before the pandemic had widespread effects on the global stock markets. The other period, which examines the CAPM during highest impact that the pandemic had, falls between March 1st, 2020 and December 31st, 2020. By examining and comparing these two periods, this study will be able to add a meaningful contribution to the pre-existing literature, as well as provide a significant contribution to the study of the validity of the CAPM. In addition, this study could add support either for, or against the model's validity, and support further studies into the matter.

1.2 Research problem

Due to the popularity and high significance of the CAPM, its validity has been examined in various markets during a wide selection of time periods, by examining if a positive linear relationship between risk and returns exists. Most of these studies, however, have been under normal market conditions. While the CAPM has been examined under past crises, such as the financial crisis of 2008, at the time of writing, no such studies have been conducted under the conditions of the Covid-19 pandemic. Moreover, many of the previous studies have focused on one or two stock markets, making it difficult to determine the validity of the model on a global scale during a selected time period. As such, in an effort to reduce the effects of a single market, this paper examines the validity of the CAPM model during a time of crises on a global scale. More specifically, it examines whether a significant difference between the returns of high and low beta stocks exists during the period between March 1st and December 31st, 2020 in the S&P 100, DAX, FTSE 100, OMX Helsinki 25, and Nikkei 225, and if it is more pronounced than in the control period between March 1st and

December 31st, 2019. These five indices provide a good selection of some of the largest companies in the world, while also diversifying the data set into different market conditions.

1.3 Research questions

To address the aforementioned research problem, the author has derived a set of research questions. These questions will answer whether a significant difference between the returns of high and low beta stocks exists. However, due to the control period before the pandemic, these questions will also answer whether such a difference exists during normal market conditions. To be able to address these two topics, this thesis will answer the following four research questions:

1. Do the daily returns of high and low beta stocks differ significantly?
2. Do the weekly returns of high and low beta stocks differ significantly?
3. Do the monthly returns of high and low beta stocks differ significantly?
4. Are the returns of high beta stocks higher during the daily, weekly, and monthly frequencies, in order to justify the higher risk?

1.4 Research objectives

To be able to answer the above research questions, the five main objectives of this study are:

1. To review the literature on the topic and present the findings of past studies, in order to gain an understanding of validity of the model.
2. To select the appropriate methodology and to design a study that will answer the research questions.
3. To calculate daily, weekly, and monthly returns of the stocks of the 20 largest companies in the S&P 100, DAX, FTSE 100, OMX Helsinki 25, and Nikkei 225.
4. To divide those companies into two different categories based on their betas. The categories being high beta stocks and low beta stocks.

5. To explore whether a significant difference between the returns of high beta stocks and low beta stocks exists both before and during the pandemic, as a means of determining if beta is a valid predictor for returns.

1.5 Structure of the study

This thesis is divided into five main sections, with every section further divided into necessary subsections. The first part is the introduction, which outlines the background for the research, as well as the research problem, research questions, and the objective of the research. The second section is the literature review, which explores past literature on the topic, and introduces the effects of the Covid-19 pandemic on the stock markets. Following that, the third section will concern the methodology of this research. In it, the data selection will be clarified, and the research method will be explained. Furthermore, the third section will present the data analysis, as well as examine the testing of the hypotheses. After that, in the fourth section, the findings of the analysis will be presented and examined. Furthermore, the fourth section will discuss and analyse those findings further. And finally, the fifth section will conclude and summarize the entirety of the thesis while providing the implications for international business. In addition, it will also bring forth the limitations of the study, as well as state the significance of it, and ultimately present the implications for further studies into the topic.

2. LITEREATURE REVIEW

This literature review examines the Capital Asset Pricing Model (henceforth CAPM) through a selection of papers that have examined the validity and effectiveness of the CAPM as a predictor of returns. In addition, the literature review studies the effects of the Covid-19 pandemic on various stock markets and the validity of the CAPM during the financial crisis of 2008, in order to discover if the model is better suited for abnormal economic conditions.

2.1 Introduction

The CAPM is arguably the best-known capital asset pricing model in use. It has been widely used since it was introduced by Sharpe (1965) and Lintner (1964). Because of its significance in the field of financial economics, it has even been called a 'paradigm' (Dempsey, 2013). The CAPM suggests that there is a positive linear relationship between risk (specifically systematic risk) and expected returns of a stock. Assuming that such a relationship is found, investors and financial managers could evaluate stocks and portfolios with a certain degree of predictability.

However, despite its popularity, the validity of the CAPM has been a point of debate ever since it was first introduced. Since the model has received a significant degree of popularity, the number of studies examining its effectiveness is also large. Although early studies found a positive linear relationship between risk and expected returns (Black, Jensen & Scholes, 1972; Fama & MacBeth, 1973; Levy, 1974), meaning that stocks with higher systematic risk (beta) were associated with higher expected returns, later studies have been unable to report such a clear relationship. Despite the inconclusive findings, the model is still widely used and taught, and as such, its validity needs to be further examined, especially during the unprecedented market conditions that the Covid-19 pandemic has brought with it.

The purpose of this literature review is to introduce the CAPM with a brief overview of its history, the general assumptions used with it, as well as its formula. In addition, the arguments for and against the CAPM will be provided. These will be followed by an examination of the validity of the model in various stock markets through papers that have studied the model with multiple approaches in both emerging markets, as well as in broad, well-established ones. After that, a section is dedicated to studying the validity of the CAPM during the financial crisis of 2008. Furthermore, the general implications, and effects that the Covid-19 pandemic has had on the stock markets will be examined. These effects will, too, be viewed from different perspectives and approaches. The parts after, will introduce a conceptual framework, as well as the hypotheses. Finally, the literature review will conclude with a summary, in addition to explaining the significance and purpose of this thesis.

2.2 Overview of the Capital Asset Pricing Model

In this section of the literature review, the author will present a brief history of the CAPM, examining its origin and use through the decades. In addition, the general assumptions needed to use the model are discussed, and the traditional formula is given and explained.

2.2.1 Brief history of the CAPM

The CAPM was first introduced in the early 60s by Treynor (1961, 1962), Sharpe (1964), Lintner (1965) and Mossin (1966). Their work was influenced by and based on earlier work in diversification and portfolio theory by Markowitz (1952). Throughout the decades and even still today, the CAPM remains popular despite the evidence against its usefulness and the selection of newer and more accurate asset pricing models. As Fama and French (2004) write, the attraction of the CAPM lies in its ability to give 'powerful and intuitively pleasing predictions about how to measure risk and the relation between expected return and risk.' The CAPM is also easy to understand because of its single factor nature and its clear and profound statement about the relationship between risk and return. As such, the model is still used and taught widely.

2.2.2 General assumptions and the formula

To be able to closely examine the model and understand its use, certain assumptions related to it need to first be introduced. The CAPM relies on the assumption that asset prices should not be influenced by all risk associated with them. As such, the risk of an asset is separated into two categories. The first one, and the one that the CAPM is not concerned about, is unsystematic, or diversifiable risk. This type of risk, while inherent to all assets, can be removed in a portfolio with adequate diversification. The second type of risk is what is known as systematic, or undiversifiable risk. Systematic risk can also be called market risk, and it assumes that no matter how well a portfolio is diversified, some risk cannot be removed. The types of risk that fall under the category of market risk might include pandemics, such as the COVID-19 pandemic, recessions, or any other type of risk that affects the entire market. This type of undiversifiable risk is what the CAPM uses as the one factor to determine return in excess of market returns.

The CAPM defines market risk with a variable called 'beta' (β). The beta of a stock is determined by its movement in relation to the market. Stocks with high betas (>1) are more volatile on average through a period of time than the general market, and stocks with low betas (<1), are less volatile on average over a period of time, when compared with the broader market. Stocks with betas of 1, have, on average, the same level of volatility as the market as a whole. Since the beta of a stock cannot be diversified away, the CAPM uses it to determine expected returns. Since the rational investor minimizes risk where possible, they require a higher rate of return for a higher level of risk. As such, stocks with high betas should provide a higher rate of return when compared with low beta stocks.

Furthermore, the CAPM relies on a 'risk-free' rate of return that needs to be established, and which extends to all investors regardless of amount invested (Fama and French, 2004). The risk-free rate of return is equal to the return of government bonds. However, there is no universal rate for risk-free return, and depending on the type of bond used, the rate could be different. For example, some could use the United States government T-bills as a proxy for the risk-free rate, while others might prefer longer, 30-year government bonds. As such, the value of the risk-free rate can never be truly known, and as interest rates change, so will the value of the risk-free rate. Finally, the CAPM requires a proxy for the return of the overall market. In order to calculate the risk premium of the market, and the value of the added risk, the expected return of the overall market needs to be determined. To be able to calculate a meaningful value for the return of the market, various indices are used. For example, the S&P 500, or the FTSE 100, could be used for determining the expected return of the market, and thusly, the risk premium. However, like the risk-free rate of return, the expected return of the market is never known, as it is constantly changing and differs depending on the market and index used.

The CAPM formula can be written as:

$$\mathbf{R_s = R_f + \beta_s (R_M - R_f)}$$

Where:

- R_s = expected return of the investment
- R_f = risk-free rate
- β_s = beta of the investment
- R_m = expected return of the market
- $R_m - R_f$ = risk premium

The CAPM can be interpreted as basing the expected return of the investment on the positive and equilibrium relationship with the difference between the risk-free rate and the market return, that is, the risk premium. Furthermore, the formula proposes that each investment would have an equal expected return, should the beta be the same. Pham (2017) adds two more hypotheses that need to be taken into consideration when using the CAPM. The first hypothesis states that markets need to be in equilibrium. For that to happen, the expected return (or in other words, price) of every asset needs to be such that investors, together, decide to hold the exact supply of that asset (Perold, 2004). The other hypothesis that is proposed by Pham (2017) states that investors' expectations of returns on assets would increase when an increase in corporate risk is apparent. This second hypothesis is further supported by the notion that for the CAPM to work, investors need to be considered as rational. When this assumption is applied to the formula, it can be deducted that as risk increases, so do expected returns. Regardless of the riskiness of the asset, the expected return of the market, as well as the risk-free rate, remain the same, and the only variable that can be adjusted is the beta. As beta increases, so do the expectations for returns. This linear relationship between risk and return can furthermore be plotted on a line called Security Market Line (SML). Assuming that the market is in equilibrium, all assets must lie on the SML (Perold, 2004).

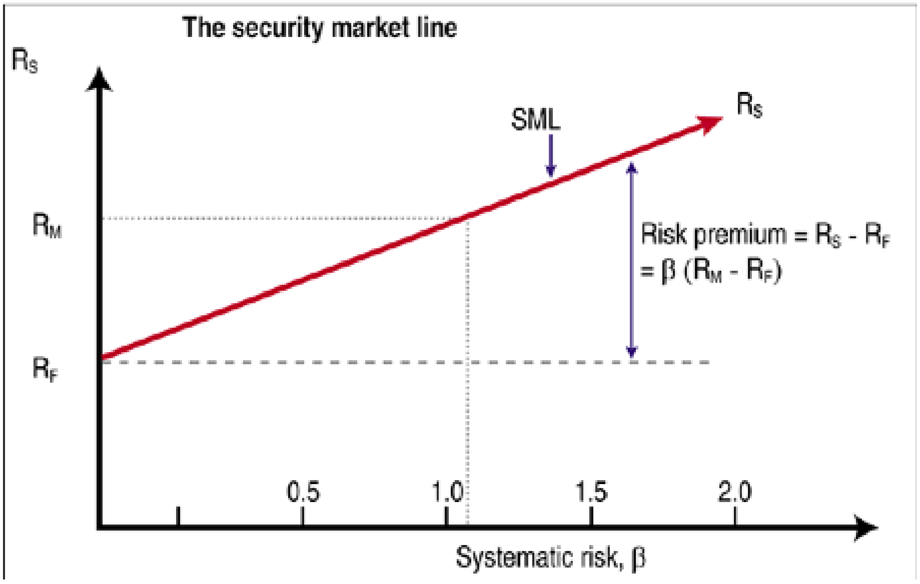

Chart 1. The security market line (Pham, 2017)

When the SML of an individual asset is presented graphically, the x-axis represents systematic risk, or beta, and the y-axis represents the expected return of an asset. The SML itself represents all the different expected returns that an asset might have depending on its systematic risk. The slope of the SML indicates the risk premium that the asset has depending on its beta. At beta 1, which the is the beta for the market, expected return for the asset, on average, equals the expected return of the market, or R_m.

2.3 Empirical evidence for and against the CAPM

Due to the popularity of the CAPM, especially in the decades following its introduction, the model has been tested repeatedly at different times and different markets. The biggest appeal of the CAPM has always been its simplicity, and because of it, the model has received significant use. However, the model does face certain limitations because of how simple it is. The most notable limitation is the one factor nature of it. The model uses only one variable, beta, when estimating expected returns. This approach has been scrutinized and disputed, and indeed, most studies have found that the one factor approach is not accurate enough, especially in periods after 1963. In response to the lack of validity in the CAPM, new factors were introduced as a means of better estimating expected returns. Fama and French (1992) combined past findings and created, what is now known as the Fama-French 3 Factor Model, as an expansion to the CAPM. They found that in addition to beta, the size of the firm, as well as its book-to-market equity, explained cross-sectional returns during the 1963-1990 period, when the CAPM failed to do so. The 3 Factor Model has since been further expanded by Fama and French in 2012. Regardless of the low accuracy of the CAPM, and the use of newer and more accurate models, it is still used as an introduction to the capital asset pricing field, and as an additional tool for technical analysis.

In the sections below, the author will provide empirical evidence both for and against the validity of the CAPM, as measured in different markets throughout the decades since its inception.

2.3.1 Evidence in support of the CAPM

Black, Jensen and Scholes (1972) were the first to conduct a large-scale study into the validity of the CAPM in the US stock market. Using a time-series model and selecting all stocks with at least 24 monthly returns available from the NYSE during the period from 1926 to 1966, they were able to 'establish the presence and significance of the beta factor in explaining security returns' (Black, Jensen & Scholes, 1972). To gain further effectiveness to their study, the selected securities were divided into ten portfolios based on the stocks' beta. Furthermore, in an effort to eliminate selection bias, the betas used to divide the stocks into portfolios, were the previous periods estimations.

Another study on the validity of risk as a predictor of returns was conducted by Fama and MacBeth (1973). Although they did not specifically test the CAPM, they were 'unable to reject the hypothesis that average returns on New York Stock Exchange common stocks reflect the attempts of risk averse investors to hold efficient portfolios.' Meaning, that on average, they found that there is a positive trade-off between risk and return, during the period between 1926 and 1968. So, while this particular study did not specifically test the validity of the CAPM, it still applies to the validity of the model, as it provides evidence for the positive relationship between risk and return.

Levy (1974), while not specifically studying the CAPM, discovered a mostly positive linear relationship between risk and returns. In the study, he divided the 500 selected NYSE stocks into 10 portfolios, each containing 50 stocks. The portfolios were based on beta estimations from previous periods, the first portfolio containing the highest beta stocks, the second containing the second highest betas, and so on. What Levy (1974) found, was that during the nine-year period between 1962 and 1970, four years provided a statistically significant positive linear relationship between risk and return. While two periods were statistically insignificant, only two provided an inverse relationship between the beta and returns. Furthermore, when the same set of portfolios were tested only under bull and bear markets, the portfolios performed as expected during bear markets. These results were statistically significant and determined that low beta portfolios performed better under bearish market conditions, experiencing smaller losses than high beta portfolios or the market. For the three bullish markets, only one year provided a statistically significant result, which further supported the positive linear relationship between risk and return, with high beta portfolios outperforming low beta portfolios. While Levy's (1974) study did not specifically examine the CAPM, the components of the study were the same. Although these results were limited by their relatively small sample size, they do provide evidence for the positive linear relationship between the risk and returns of stocks, which is what the CAPM relies on.

Thus far, however, all the empirical evidence presented has been from the 70s, and market conditions, as well as the number of studies examining the CAPM, have changed. Indeed, most recent studies have been unable to find a relationship between just risk and returns. However, there are some more recent studies that support the relationship proposed by the CAPM.

Lam (2001) found a strong correlation between betas and returns in the Hong Kong stock market. Contradicting the results of previous studies, he found that 'there is a strong relationship between positive betas and returns in up markets and also a strong relationship between negative betas and returns in down markets.' Lam (2001) concluded that the CAPM had proved to be a valid equilibrium pricing model in the Hong Kong stock market.

Another more recent study examining the validity of the CAPM was conducted by Ihnatov and Sprincean (2015). They compared the validity of the model in the stock markets of USA, Poland, and Romania. While they found statistical validity for the model in all three markets, the sample size was small, with only 10 stocks selected from the New York and Warsaw exchanges, and only seven being selected from the Bucharest market in Romania. Contrary to the theory supporting the CAPM, Ihnatov and Sprincean (2015) found that the highest correlation between the estimated return of the CAPM and the effective return, was in the NYSE and Nasdaq. For the CAPM to work, markets would need to provide a certain level of predictability. Since beta from a previous period is used to predict the future, markets need to be weak form efficient for patterns and predictability to emerge. The CAPM, which is a tool for technical analysis, should not work in developed, semi-strong form efficient markets, such as the NYSE, where prices change randomly to reflect any and all new public information. However, since any market can display tendencies of weak-form efficiency for a period of time, it is possible that the US exchanges behaved more like other weak form efficient markets during the study period.

However, there is also another more recent study that supports the use of beta as a predictor of expected returns. Pettengill, Sundaram and Mathur (1995) found, contrary to many previous tests, that a systematic relation between beta and returns exists. The data for their study came from the CRSP monthly database and extended from 1926 to 1990. While most studies conducted after the periods of 1963 found that beta alone was not an effective predictor of returns, what Pettengill, Sundaram and Mathur (1995) found, seems to contradict those findings. Their approach to testing the relation between beta and returns relied on a positive relation during up markets and a negative relation during down markets, while other studies usually assumed an always positive relation between the two. An approach that Pettengill, Sundaram and Mathur (1995) claim to be ‘biased’.

Author (s)	Year	Findings	Methodology
Black, Jensen & Scholes	1972	Were able to find a significant relationship between beta and security returns during the period between 1926 and 1966 in the NYSE.	Time series regression
Fama & MacBeth	1973	Found that, on average, a postive trade-off between risk and return existed between 1926 and 1968 in the NYSE.	Two-parameter model & risk-return regression
Levy	1974	Discovered a mostly positive linear relationship between risk and return between 1962 and 1970 in the NYSE.	Regression & correlation
Pettengill, Sundaram & Mathur	1995	Found that a systematic relation between beta and returns exists between 1926 and 1990, contradicting the findings that the CAPM had not been valid after 1963.	Modified three-step portfolio approach & regression
Lam	2001	Found a strong correlation between betas and returns in the Hong Kong stock market between 1980 and 1995.	Modified three-step portfolio approach
Ihnatov & Sprincean	2015	Found statistical validity for the CAPM in the stock markets of the US, Poland and Romania between 2009 and 2013.	Regression

Table 1: Summary of studies in support of the CAPM

2.3.2 Evidence against the CAPM

Most evidence for the validity of the CAPM either comes from the 70s, or from markets that display weak form efficiency. However, studies into the model and its accuracy have been conducted regularly and most papers propose new variables to be added to the basic capital asset pricing model.

Most notably, Fama and French (1992) found that during periods after 1963, the relationship between beta and returns disappeared. They proposed that two other variables be used in addition to beta. In their model, now known as the Fama-French 3 Factor Model, the size of the firm, as well as the book-to-market equity, do a superior job of capturing cross-sectional variation in stock returns when compared with the CAPM. The Fama-French 3 Factor Model suggests that smaller companies generally generate higher returns than larger companies, and that companies with higher book-to-market ratios have improved returns over the market. Adding these factors to the original CAPM allows for a more accurate representation of expected future returns, as it considers other factors besides just risk. However, since the Fama-French model still uses beta as measure, it could be argued that it cannot be completely accurate either. Since future betas cannot be estimated with certainty, betas from previous periods are used. Even if the data from the previous periods is reliable, predicting future returns with past information is always problematic. This problem becomes especially apparent in developed and semi-strong form efficient markets. Since these markets should always reflect all publicly available information, no patterns in stock prices should emerge. In practice, this means that price changes happen randomly, and all form of technical analysis is useless.

Nevertheless, in support of the findings of Fama and French (1992), Miles and Timmermann (1996) found that size, as well as book-to-market ratios, systematically helped explain subsequent excess returns in the UK markets. In their study they used data from the Extel company accounts and from the London Business School share price data tapes. From these sets of data, they were able to construct a set of 477 companies excluding all financial companies, reporting in all financial years between 1975 and 1990. Although Miles and Timmermann (1996) were able to find a relationship between company size, book-to-market ratio, and the expected returns, they were unable to answer why these aspects of a company were a better measure of risk than beta.

Before the seminal paper by Fama and French (1992), Banz (1981) did his own study on the significance of company size on the expected returns. He found that ‘the CAPM is mis specified’ and that small companies generally had much higher risk-adjusted returns than large companies on the NYSE. However, while his findings, which were found from a sample of all common stocks on the NYSE that were quoted for at least five years during 1926 - 1975, were significant, he was unable to explain why such an effect exists. Banz (1981) writes, ‘There is no theoretical foundation for such an effect.’ Despite the uncertainty surrounding the reason for the size effect, the findings were of such magnitude that they undermine the use of only beta as a predictor of returns, and have since been adopted into the Fama-French model.

Furthermore, two years later, Basu (1983) found that during the period between 1963 and 1980, returns on the common stock of NYSE were related to both size and the company’s earnings yield. His findings indicated that stocks with a higher earnings yield (E/P) tended to earn higher risk-adjusted returns than companies with lower E/P. He, like Banz (1981) before him, found that smaller companies generally earned significantly higher returns than large companies, but he also found that the size effect became practically of no importance ‘when returns were controlled for differences in risk and E/P ratios.’

Results from other, less developed markets than the NYSE, further support the conclusion that the validity of the CAPM is weak. Dajcman, Festic and Kavkler (2013) recently found that the validity of the CAPM in the Slovenian, Hungarian and Czech Republican markets was weak. These findings indicate that even in smaller, younger markets, where market efficiency might be lower and trends might emerge, the CAPM is not an accurate model for predicting expected returns. The data for the study came from the LJSEX index for Slovenia, BUX for Hungary and PX for the Czech Republic, and the observations began in 2002, 1997 and 1995, respectively, and ended in 2010.

Despite all the evidence for and against the CAPM, it is often the first model taught for asset pricing because it is easy to understand and conceptualize. As Fama and French (2004) note, the CAPM is a 'theoretical tour de force' and is often used as an introduction to concepts of portfolio theory. However, despite the easy access and ease of use, the CAPM does face empirical uncertainty. Although there is old and new research attempting to conclusively determine the validity of the model, results on both sides keep appearing. Because of the lack of a clear answer, the use of the CAPM in application should be approached with caution, and results from it should, at most, be used in conjunction with other models of fundamental and technical analysis.

Author (s)	**Year**	**Findings**	**Methodology**
Banz	1981	Found that the CAPM is 'mis-specified' and that small companies generally had much higher risk-adjusted returns, when compared with large companies, in the NYSE between 1936 and 1975.	Generalized least squares regression (GLS)
Basu	1983	Found that between 1963 and 1980, the returns of the common stocks on the NYSE were related to the size of the company, as well as its earnings yield.	Hotelling's test
Fama & French	1992	Discovered that during the period between 1963 and 1990, the relationship between beta and returns disappeared in NYSE, AMEX and NASDAQ. Furthermore, they propsed that two other variables, the size of the firm and the book-to-market equity, be used in addition to the beta.	Fama-MacBeth regression
Miles & Timmermann	1996	Found that the size of the firm, as well as the book-to-market ratios systematically helped explain excess returns in the UK markets between 1975 and 1990.	Fama-MacBeth regression, non-parametric Monte Carlo simulation
Dajcman, Festic, Kavkler	2013	Discovered that the validity of the CAPM in the Slovenian market between 2002 and 2010, the Hungarian market between 1997 and 2010 and Czech Republican market between 1995 and 2010, was weak	Time series regression, cross-sectional regression

Table 2: Summary of studies with evidence against the CAPM

2.4 CAPM during the financial crisis of 2008

To have a better understanding of how the CAPM has performed during previous one-off events affecting the entire market, a brief introduction to the validity of the model during the 2008 subprime mortgage crisis will be provided.

Fatnassi and Hasnaoui (2014) found that the mean beta in such industries as consumer staples, energy, financials, IT, and telecom services rose during the crisis period between August 2007 and February 2009 in the US. The financial sector, in particular, experienced a significant increase in systematic risk, averaging a beta of around 1.6 during the crisis period, an increase of about 0.6 from the pre-crisis period. Interestingly, the highest expected returns during the August 2007 and February 2009 period came from the consumer discretionary and health care industries, which both saw their betas decline during the crisis period. These findings would indicate that the CAPM is of little value during a one-off event. If industries with decreasing systematic risk report highest expected returns, the foundational principle of the model (higher risk equals higher return) is reversed. Assuming that similar trends emerge from the Covid-19 pandemic, the findings of Fatnassi and Hasnaoui (2014) would receive further support.

Similarly, Curran and Velic (2020) found that at shorter time horizons, during periods of high volatility, the positive relation between risk and reward can 'collapse'. Indeed, through their data set which covered over 80 countries, they found that during the five-year period before the 2008 crisis, between 2003 and 2007, the correlation between systematic risk and returns was positive and high, with a rank correlation of 0.60. However, during the recessionary, crisis period between 2008 and 2012, the relation turned negative with a rank correlation of -0.27. Further evidence for the inverse relation between systematic risk and returns as a result of periods of high volatility, is provided by the returning positive relation during the period between 2013 and 2017. Like Fatnassi and Hasnaoui (2014), Curran and Velic (2020) provide evidence against the validity of the CAPM during one-off events, such as the 2008 subprime mortgage crisis.

2.5 Effects of the Covid-19 pandemic on stock markets

The goal of this thesis is to examine the validity of the CAPM during a time of extremely rare market conditions. The Covid-19 pandemic has affected all stock markets around the world, and its effects have forced the markets into an unprecedented environment. Since the validity of the CAPM will be examined both during a period before the pandemic, and a period during the pandemic, a closer look at what the implications of Covid-19 to the markets has been, is needed. As such, the discussion below will examine the effects of the Covid-19 pandemic on stock markets.

The Covid-19 pandemic began in China during December 2019. While the pandemic had already started to spread throughout the world, the implications of it became evident in the stock markets towards the end of February 2020. Using the S&P 500 as an example, the first significant decrease began on February 24th and continued until the 28th. Interestingly, after the 12% drop experienced during those four days, the index bounced slightly up, until March 4th, after which the most significant decrease in value started. From the 4th up until the 23rd, the S&P 500 saw a 25% decrease in value. However, despite the magnitude of the pandemic, stock indices quickly started to climb afterwards. Indeed, by early September, the S&P 500 had already climbed 60%, despite the pandemic still infecting more and more people.

In their study of the impacts of Covid-19 on 20 leading indices, Sinha, Jalan and Singh (2020) examined the effects of the pandemic during four different periods. The first period, defined as the normal period, acted as a control for the periods near and during the pandemic. It stretched from January 1st, 2019 to December 30th, 2019. During the pre-pandemic period, the 20 indices all recorded positive mean returns, ranging from 0.01% a day in the SETI index, to 0.12% in NZX 50. However, during the pre-event window (February 25th, 2020 – March 11th, 2020) and the post-event window (March 12th, 2020 – March 26th, 2020), nearly all indices experienced negative mean returns. In fact, during the pre-event window, all indices saw negative returns, indicating a quick reaction from the stock markets. This pre-event window examined how the markets reacted before the pandemic was officially declared as such by the WHO. However, already in the post-event window, some indices, such as the CAC 40, UK FTSE 100, S68.SI and IMOEX.ME, experienced positive mean returns. Supporting the idea that stock markets react quickly and fully to news, in the long-term post-event window (March 12th, 2020 – June 12th, 2020), almost all indices were already reporting positive mean returns. In fact, only the SSE composite, NSEI, S68.SI and MXX, posted negative mean daily returns.

Zhang, Hu, and Ji (2020) explored the risk of the stock markets in the nine countries with the highest number of infections together with Japan, Korea, and Singapore, in the form of standard deviation. The average standard deviation between the countries increased from 0.0071 in February, to 0.0196 in March. The outlier of the group was China, which moved from having the highest standard deviation in February 2020, to having the lowest in March 2020. The other 11 countries saw an increase in standard deviation in daily returns. Since China was the first country to experience the pandemic, and dealt with it with the most aggressive approach, it is apparent why it was the only country to experience a decline in stock market risk during March. Furthermore, Khan, Zhao, Zhang et al. (2020) found that growth in weekly Covid-19 cases had a negative impact on returns during the subsequent week. They also discovered that during the early stages of the pandemic, stock markets had a very subdued reaction to it, and did, in fact, perform even better than during the normal period.

2.6 Hypotheses

Based on the discussion above, about the validity of the CAPM, as well as the general impacts that the Covid-19 pandemic has had on the stock markets, the following empirical study will attempt to find an answer to the hypotheses presented below:

The first three hypotheses answer the question about the validity of the CAPM during normal market conditions. The assumption, and thus the null hypothesis, is that the daily, weekly, and monthly returns are not significantly different, as supported by the findings of Banz (1981), Basu (1983), Fama and French (1992), Miles and Timmermann (1996), and Dajcman, Festic and Kavkler (2013).

H_{01}: The daily returns of high and low beta stocks are not significantly different in the control period from March 1st, 2019 to December 31st, 2019.

H_1: The daily returns of high and low beta stocks are significantly different in the control period from March 1st, 2019 to December 31st, 2019.

H_{02}: The weekly returns of high and low beta stocks are not significantly different in the control period from March 1st, 2019 to December 31st, 2019.

H_2: The weekly returns of high and low beta stocks are significantly different in the control period from March 1st, 2019 to December 31st, 2019.

H_{03}: The monthly returns of high and low beta stocks are not significantly different in the control period from March 1st, 2019 to December 31st, 2019.

H_3: The monthly returns of high and low beta stocks are significantly different in the control period from March 1st, 2019 to December 31st, 2019.

The next three hypotheses answer the question about the validity of the CAPM during unusual and rare market conditions, in this case, the Covid-19 pandemic. The null hypotheses, as supported by Fatnassi and Hasnaoui (2014) and Curran and Velic (2020), is that the returns of high and low beta stocks are not significantly different during the pandemic period.

H_{04}: The daily returns of high and low beta stocks are not significantly different in the pandemic period from March 1st, 2020 to December 31st, 2020.

H_4: The daily returns of high and low beta stocks are significantly different in the pandemic period from March 1st, 2020 to December 31st, 2020.

H_{05}: The weekly returns of high and low beta stocks are not significantly different in the pandemic period from March 1st, 2020 to December 31st, 2020.

H_5: The weekly returns of high and low beta stocks are significantly different in the pandemic period from March 1st, 2020 to December 31st, 2020.

H_{06}: The monthly returns of high and low beta stocks are not significantly different in the pandemic period from March 1st, 2020 to December 31st, 2020.

H_6: The monthly returns of high and low beta stocks are significantly different in the pandemic period from March 1st, 2020 to December 31st, 2020.

2.7 Conceptual framework

To conceptualize the goal of this study, the conceptual framework will explain the relationship between risk and return. Furthermore, it will act as a guide for the research into the question of whether the CAPM is valid as a model for asset pricing during a time of crisis. Since the research will revolve around calculating expected returns based on historical data and approximating a beta value, understanding the CAPM, and the relationship between risk and return, is of high importance, as it provides a way of examining if a positive linear relationship between risk and return exists.

As such, the conceptual framework will display the research goal in a simple and easy to understand way, while also presenting the relationship between the expected return of the investment and its beta, as well as providing a clear differentiation between the two periods examined.

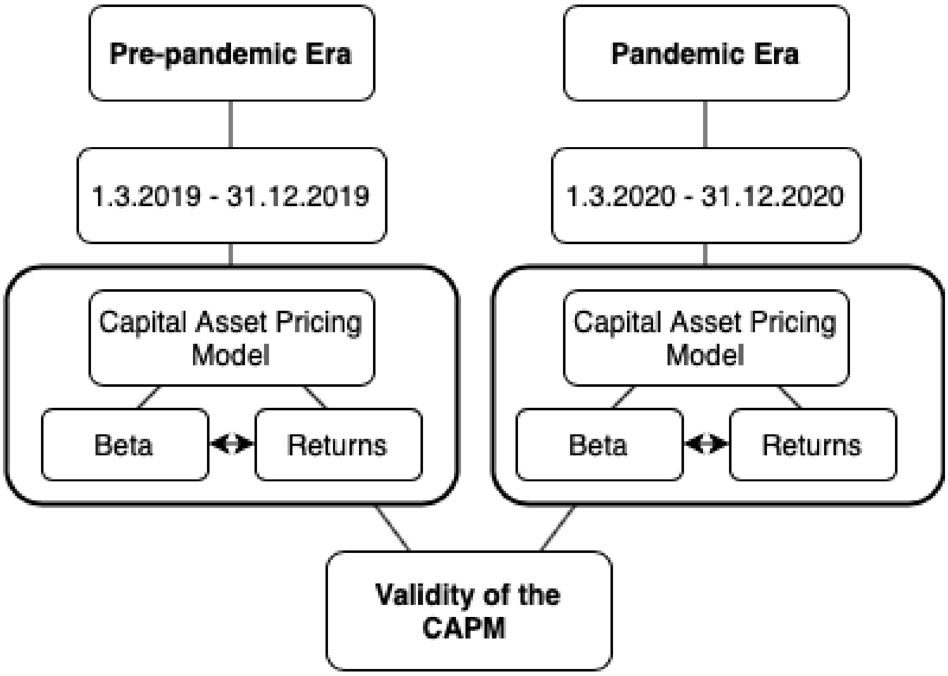

Chart 2. Conceptual framework on the CAPM (Airinen, 2020)

2.8 Conclusion

The purpose of this literature review has been to outline and to give a general understanding of the Capital Asset Pricing Model, its strengths, and weaknesses, as well as its role in the financial field. Furthermore, this literature review has attempted to provide an outlook into the past studies about the model and its validity.

While the CAPM has been, and still is, central in capital asset pricing and estimations of return, it is not without its problems. Due to its simplistic nature and ease of use, the model has enjoyed popularity since its inception. It is still used alongside other methods and models, and it is often the first touch that finance students get into the asset pricing models and efficient portfolio theory. However, despite having found early success in empirical tests, it has since been subjected to a number of tests that have been unable to confirm its validity. As a model that is built upon the idea that beta alone can predict future returns, it has received updates and iterations that have added further elements to it, in an attempt to create a more accurate model. While most studies into the validity of the CAPM have been conducted in the US stock markets, studies in smaller and less developed markets have also been done. Interestingly, regardless of the market conditions, the validity of the CAPM has received both support and arguments against it. Although the literature presented above does slightly favour the evidence for the validity of the model, it should be noted that most of the studies arguing in favour of the CAPM, examined stock markets before the period of 1963. However, most studies after 1963 have been unable to find support for the positive linear relationship between risk and return.

So far, there have been no studies about the validity of the CAPM during the Covid-19 pandemic. Since the market conditions created by the pandemic are extremely rare and unique, there is a possibility to examine if the model is valid during such market conditions. Past studies of systematic risk and returns during times of crisis, in particular the financial crisis of 2008, provide an insight into how the CAPM might behave during the Covid-19 pandemic. If those findings remain true, the validity of the model during one-off events would be in question. As such, the following thesis will examine the relationship between systematic risk and returns during two periods. More specifically, the validity of the CAPM will be examined through a comparison between a period before the pandemic and one during it, by testing for a difference between the daily, weekly, and monthly returns of high and low beta stocks. Since pandemics, or any other unforeseeable disasters that concern the whole world, are so rare, this situation provides a possibility to examine how unusual market conditions impact the validity of the model. Hopefully, this empirical test will provide an answer about the validity of the model during normal market conditions, but also during times of high volatility and uncertainty. The research will provide benefits to investors looking to use the CAPM as a means of evaluating stocks and efficient portfolios, as well as giving other researchers a further view into the validity of the model.

3. METHODOLOGY

This chapter is made in order to clarify and give more insight into the process of addressing the hypotheses. It will include sections that discuss the selected time periods, the selected stocks, the sources for the financial data, as well as the benchmarks that individual stock returns will be compared to. Following that, this chapter will introduce some of the most common methods when examining the validity of the CAPM. In addition, the method of this research, the two-tailed t-test, will be discussed. Finally, the chapter will conclude with the data analysis.

3.1 Data selection

The following sections will introduce the selected periods in more detail and explain the reasoning behind the selection, the selected stocks, the sources for the data, as well as the benchmarks that the returns will be compared to, in order to calculate the estimated betas.

3.1.1 Selected periods

The purpose of this study is to examine the validity of the CAPM on a global scale during a time of crises. The selected crisis is the Covid-19 pandemic, that affected stock markets globally. To be able to determine not only the validity of the model during such a rare market circumstance, but to also determine if the model performed better under such conditions, a control period under normal market conditions has also been selected. The period under the pandemic is from March 1st to December 31st, 2020. When examining the effects of the 2008 financial crisis, Fatnassi and Hasnaoui (2014) also used a relatively short period of time for the crisis period. Like this study, they did so in order to effectively compare the effects of the period of increased volatility, with normal market conditions. Furthermore, the reasoning behind this particular period of time comes from the effects of the pandemic on most stock markets. While Covid-19 had already started in China in late 2019, the most significant effects on most stock markets came in early March in 2020. As such, the selected period encompasses both the drastic drop that most stock markets experienced, as well as the rapid rise that took place during the remaining year. In an effort to produce a fair comparison between the pandemic period and the control period, the control period is between March 1st and December 31st, 2019. This is done in an effort reduce the effect of market anomalies, such as the January effect, or any others that might be tied into a certain period of time. Sinha, Jalan and Singh (2020), used a similar control period in their study of the effects of the Covid-19 pandemic on stock markets, expanding from January 1st, 2020, to December 30th, 2020. Using two periods that encompass the same length and time of year, should lead to more accurate and meaningful results. Furthermore, due to the scope and time limitations of the study, the data set for the control period has been limited.

3.1.2 Selected stocks

In order to gain a global understanding of the validity of the CAPM, five countries and indices were selected. They include the S&P 100 in the United States, the DAX in Germany, the FTSE 100 in the United Kingdom, the OMX Helsinki 25 in Finland, and the Nikkei 225 in Japan. While the OMX Helsinki 25 does not provide results for a globally significant market, it does explain how the pandemic affects the validity of the CAPM in a smaller market. In addition to providing a global outlook into the validity of the model, this selection of indices also encompasses countries with a varying level of success in their response to the Covid-19 pandemic (McKenzie and Adams, 2020). Furthermore, this selection could alleviate the effects of other significant events, such as the Brexit in the UK, or the presidential election in the US, by combining the companies in their respective markets with the other indices.

From each of the indices mentioned, the author selected the 20 largest companies by market capitalization. One of the reasons for selecting 20 companies from each index was the structure of the indices themselves. All but the Nikkei 225 are market capitalization weighted. As such, the 20 largest companies by market capitalization, are also the most significant parts of the index. Furthermore, the DAX and the OMX Helsinki 25 only have 30 and 25 companies in them, respectively. As such, the 20 selected companies provide a comprehensive explanation of the index, and as such, market returns. In addition, the number of selected companies was limited to 20 due to the time restrictions of the study. The selected companies also provide a wide selection of industries represented, giving a better understanding of the model and its validity while minimising the effects of certain industries performing better than others. In order to calculate the daily, weekly, and monthly returns, historical prices for each stock were collected from https://finance.yahoo.com, and the calculated returns were used to test the hypotheses.

Table 3: The 20 largest stocks from the S&P 100, DAX, FTSE 100, OMX Helsinki 25, and Nikkei 225.

	S&P 100	DAX	FTSE 100	OMX Helsinki 25	Nikkei 225
Tickers	AAPL	SAP.DE	ULVR.L	NESTE.HE	7203.T
	MSFT	LIN.DE	AZN.L	KNEBV.HE	9984.T
	AMZN	SIE.DE	HSBA.L	NDA-FI.HE	6758.T
	GOOG	VOW3.DE	RIO.L	SAMPO.HE	9432.T
	FB	ALV.DE	DGE.L	FORTUM.HE	9983.T
	BRK-A	DAI.DE	BP.L	NOKIA.HE	6098.T
	TSLA	DTE.DE	RDSA.L	UPM.HE	9433.T
	V	BAS.DE	GSK.L	TELIA1.HE	4519.T
	JPM	MRK.DE	BATS.L	STERV.HE	4063.T
	JNJ	ADS.DE	BHP.L	KESKOA.HE	8306.T
	WMT	DPW.DE	RB.L	ELISA.HE	8035.T
	MA	BAYN.DE	AAL.L	MOCORP.HE	6367.T
	DIS	BMW.DE	LSEG.L	WRT1V.HE	4568.T
	UNH	IFX.DE	PRU.L	ORNBV.HE	4502.T
	BAC	MUV2.DE	GLEN.L	TYRES.HE	7267.T
	PG	HEN.DE	VOD.L	VALMT.HE	8316.T
	NVDA	VNA.DE	REL.L	HUH1V.HE	6902.T
	PYPL	CON.DE	BARC.L	KOJAMO.HE	6501.T
	HD	DB1.DE	NG.L	SSABBH.HE	8001.T
	XOM	DBK.DE	LLOY.L	METSA.HE	6954.T

3.1.3 Selected financial data sources

This thesis is based on secondary data, which was acquired from https://finance.yahoo.com. From there, adjusted returns were collected for each selected stock, and from those values, the actual returns were calculated. The computed values were used in the simple linear regression alongside the returns of the benchmark indices to arrive at the beta for each stock in both the control and pandemic period, in all three frequencies (daily, weekly, and monthly).

3.1.4 Selected benchmark indices

In order to test the validity of the CAPM model, one of its elements needs to be determined. Without the proxy for the return of the market, the model would not work, and thus, the validity of the model could not be tested. As such, to be able to compute the betas of the stocks, proxies for market returns need to be determined. Typically, a stock index acts as a proxy for the market, as it is indicative of the performance of a large selection of stocks and industries. Since this study examines five different markets in order to determine the validity of the CAPM, five proxies have been selected. When examining the validity of the CAPM in the Vietnamese stock market, Pham (2017), similarly, used two market proxies for the two stock indices that were used. Furthermore, Dajcman, Festic and Kavkler (2011) use a similar method, using three indices as proxies for each market portfolio. The five selected indices for this study are the S&P 100 for the US stock market, the DAX for the German stock market, the FTSE 100 for the UK stock market, the OMX Helsinki 25 for the Finnish stock market, and the Nikkei 225 for the Japanese stock market. Each selected index provides a wide selection of industries and stocks in their respective markets and, as such, provides a meaningful comparison between the individual stocks and the market as a whole. The returns of each of the 20 stocks in each index will be compared to their respective proxy, and by using simple linear regression their betas will be calculated.

3.2 Research method

This sub-chapter will provide a cohesive view of the structure of the research and the methodology used to determine the validity of the Capital Asset Pricing Model both in the control period prior to the pandemic, as well as the period during the pandemic. The following step by step explanation of the process should help the reader better follow the research.

Using previous literature as a basis, simple linear regression is used to determine the betas of each stock for daily, weekly, and monthly data in the control period, as well as in the pandemic period. The betas are calculated using simple linear regression, as it also provides the statistical significance of the calculated beta values. Furthermore, in order to determine if there is a significant difference between low and high beta stocks, a two-tailed t-test is used to determine the significance of the difference, as well as the direction of it.

- *Step 1*: Collect daily, weekly, and monthly historical prices for the 100 selected stocks during the control period between March 1st, 2019 and December 31st, 2019, as well as during the pandemic period between March 1st, 2020 and December 31st, 2020.
- *Step 2*: Estimate the daily, weekly, and monthly rates of return for each stock in both periods by calculating the logarithmic return in Excel.
- *Step 3*: Calculate daily, weekly, and monthly betas for each stock in both periods using simple linear regression in Excel.
- *Step4*: Separate high beta stocks and low beta stocks into their own groups for daily, weekly, and monthly returns, in both periods.
- *Step 5*: Estimate the difference between high and low beta stocks, as well as the direction of it, by using the two-tailed t-test in Excel.
- *Step 6*: Test the hypotheses.

3.3 Data analysis

The following sub-chapters will provide a more detailed explanation of the methods used to determine the estimated returns, as well as the betas.

3.3.1 Return estimations

The daily, weekly, and monthly returns for each stock were calculated by using the logarithmic return. This was done due to the nature of the stock and index returns. These returns are, in theory, infinite and continuous, and as such, the logarithmic return, which compounds returns continuously, was used. Furthermore, the logarithmic return is symmetrical, meaning that gains and losses are equally weighted. Simple returns, while easier to calculate and interpret, are asymmetrical, meaning that gains have a heavier weight than losses. Thus, logarithmic returns are more accurate.

$$\mathbf{R_{s,\,t} = \ln\,(P_{s,\,t+1}\,/\,P_{s,\,t})} \qquad \mathbf{(1)}$$

Where:

$R_{s,\,t}$: the daily/weekly/monthly return of the stock in day/week/month t

$P_{s,\,t+1}$: the price of the stock in day/week/month t+1

$P_{s,\,t}$: the price of the stock in day/week/month t

Similarly, to calculate the returns of the indices, meaning proxies for the market, the same formula was used with slight changes to the variables:

$$\mathbf{R_{m,\,t} = ln\ (P_{m,\,t+1} / P_{m,\,t})} \qquad \textbf{(2)}$$

Where:

$R_{m,\,t}$: the daily/weekly/monthly return of the index in day/week/month t

$P_{m,\,t+1}$: the price of the index in day/week/month t+1

$P_{m,\,t}$: the price of the index in day/week/month t

3.3.2 Beta estimations

To calculate the estimated beta of each stock from daily, weekly, and monthly data for both the control period and the pandemic period, simple linear regression through Excel is used. The estimated returns of the stock are used as the input for the y range, and the estimated returns of the index are used as the x range. A 95% confidence level is used to determine and select beta values that can be estimated with statistical significance. The coefficient of the x variable tells the slope of the equation and, in this case, the beta of the stock. Only betas with a p-value of less than 0.05 were used. This was done in an effort to further increase the significance of the findings. By limiting the betas to only those that were statistically significant, the results of the t-tests can be interpreted with a higher degree of confidence. As such, high or low betas with a p-value of less than 0.05, were omitted from the data used for the t-tests.

To separate the betas into high and low beta stocks, high beta stocks were considered as having betas equal or higher than 1.50, and low beta stocks were considered as having betas equal or lower than 0.80. Levy (1974), in his study of the validity of the CAPM, ranked betas of the selected stocks into 10 deciles. Using the data from his study, stocks with a beta equal or less than 0.80 make up about 30% of the selected stocks, while stocks with a beta equal or higher than 1.50 make up about 20%. As such, defining high and low beta stocks in this way, should result in a relatively large data set, while also providing significant differences to the market returns. High beta stocks being 50% more volatile, and low beta stocks being 20% less volatile, than the market.

3.4 Testing hypotheses

In order to test the hypotheses, a two-tailed t-test assuming unequal variances between the average daily/weekly/monthly returns of high beta stocks (variable 1) and the average daily/weekly/monthly returns of low beta stocks (variable 2) was conducted. The two-tailed t-tests were done for both the control period, and the pandemic period. The two-tailed t-test was used as it explains the amount of difference between the two variables used. Since the CAPM states that for an increased level of risk, beta, the investor should expect a higher level of returns, determining whether a significant level of difference between the returns of high and low beta stocks exists, explains if the CAPM is valid. Assuming that there is a significant degree of difference between the returns of high and low beta stocks, then the idea that a higher beta introduces more volatility holds true, volatility measured as the standard deviation of individual stock returns. Moreover, assuming that the betas are positive and higher than the market beta of 1, these stocks should experience higher returns than stocks with betas less than 1, when market conditions are bullish.

The two-tailed t-tests assuming unequal variance are done through Excel and to determine if the results are significant, the absolute value of the t-stat should be higher than the value of the t critical for one tail. However, while the results can be statistically significant with a negative t-stat value, in order to support the hypothesis of the CAPM, that a higher beta and a higher level of risk equals higher returns, the t-stat value should be a positive one, as it would indicate that the average returns of high beta stocks have been higher than those of low beta stocks. During market downturns it is possible that low beta stocks experience higher returns as they are less volatile, and as such, the t-stat could be negative and still support the theory behind the CAPM. For the selected research periods, however, the t-stat value should be positive, as both periods were dominated by a positive trend in the markets, apart from the significant downturn in the beginning of the pandemic period.

The hypotheses of the research are as follows:

H_1: The daily returns of high and low beta stocks are significantly different in the control period from March 1st, 2019 to December 31st, 2019.

H_2: The weekly returns of high and low beta stocks are significantly different in the control period from March 1st, 2019 to December 31st, 2019.

H_3: The monthly returns of high and low beta stocks are significantly different in the control period from March 1st, 2019 to December 31st, 2019.

H_4: The daily returns of high and low beta stocks are significantly different in the pandemic period from March 1st, 2020 to December 31st, 2020.

H_5: The weekly returns of high and low beta stocks are significantly different in the pandemic period from March 1st, 2020 to December 31st, 2020.

H_6: The monthly returns of high and low beta stocks are significantly different in the pandemic period from March 1st, 2020 to December 31st, 2020.

3.5 Assumptions and limitations of the t-test

When using the t-test, certain assumptions need to be made. The t-test assumes that the data is from a random sample. In the case of this study, this holds true, to an extent, as the selected companies, and indices, are a representative sample of the total population. However, it should be noted that the companies in each index were selected by their market capitalization, thus making the selection not truly random. The t-test also assumes that the data has a normal distribution when plotted. Furthermore, the data set is assumed to be large, as it can be assumed that when the size of the data set increases, the distribution approaches a normal distribution. The original data set consisted of 100 companies in two periods, during three time-frequencies. However, it was reduced due to the use of returns of companies with statistically significant betas. Nonetheless, the data set remains relatively large, indicating that it is moving towards a normal distribution.

The most significant limitation of the t-test is the loss in degrees of freedom. As the degrees of freedom decrease, the required t-stat to produce statistically significant results increases. This limitation is particularly relevant for this study, as the two-tailed t-test assuming unequal variances is used. When assuming unequal variances, the variances will increase, leading to a lower degree of freedom when compared with a two-tailed t-test assuming equal variances.

The assumptions and limitations are summarized below:

- Sample needs to be random, and representative of the total population
- Data has a normal distribution when plotted
- Data set is large, as it can be assumed that when the size of the data set increases, it moves towards a normal distribution
- Lower degrees of freedom, leading into a higher required t-stat

4. FINDINGS

This section of the thesis will present the findings of the research. It will begin by presenting the estimated rates of return of the individual stocks for daily, weekly, and monthly frequencies. It will then proceed to display the estimated beta values of individual stocks for the three time-frequencies. Another sub-chapter is dedicated to presenting the companies that had beta values either equal or higher than 1.50, or equal or lower than 0.80, that were also statistically significant. Ultimately, this chapter will conclude with an examination of the two-tailed t-tests that were done for the applicable companies for daily, weekly, and monthly frequencies.

4.1 Rates of return for individual stocks

The following sections will display the calculated estimated returns for the individual stocks traded on the S&P 100, DAX, FTSE 100, OMX Helsinki 25, and Nikkei 225 for the daily, weekly, and monthly frequencies.

4.1.1 Daily rates of return

Table 4: Daily average rates of return for the 100 stocks traded on the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225 for both the control period and the pandemic period.

S&P 100 DAILY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
AAPL	0,24816 %	0,28430 %	WMT	0,10394 %	0,11233 %
MSFT	0,16533 %	0,12764 %	MA	0,13044 %	0,06018 %
AMZN	0,04745 %	0,25272 %	DIS	0,11623 %	0,18596 %
GOOG	0,07519 %	0,11234 %	UNH	0,09233 %	0,12228 %
FB	0,10991 %	0,16327 %	BAC	0,09481 %	0,02287 %
BRK-A	0,05020 %	0,02892 %	PG	0,12118 %	0,07855 %
TSLA	0,16252 %	0,71390 %	NVDA	0,18964 %	0,29931 %
V	0,11100 %	0,05390 %	PYPL	0,04226 %	0,34114 %
JPM	0,14569 %	0,02742 %	HD	0,08901 %	0,08081 %
JNJ	0,03343 %	0,05550 %	XOM	-0,05012 %	-0,09716 %

DAX DAILY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
SAP.DE	0,12058 %	-0,01832 %	DPW.DE	0,12517 %	0,23317 %
LIN.DE	0,12338 %	0,10518 %	BAYN.DE	0,03159 %	-0,12300 %
SIE.DE	0,08853 %	0,11745 %	BMW.DE	0,01426 %	0,13931 %
VOW3.DE	0,08023 %	0,02629 %	IFX.DE	0,01564 %	0,24950 %
ALV.DE	0,06991 %	0,04418 %	MUV2.DE	0,13201 %	0,03719 %
DAI.DE	-0,00488 %	0,24776 %	HEN.DE	0,01440 %	0,03818 %
DTE.DE	0,02366 %	0,04597 %	VNA.DE	0,07177 %	0,10988 %
BAS.DE	0,01655 %	0,16084 %	CON.DE	-0,09902 %	0,14722 %
MRK.DE	0,06866 %	0,11016 %	DB1.DE	0,11440 %	-0,01222 %
ADS.DE	0,14802 %	0,09345 %	DBK.DE	-0,07196 %	0,08247 %

FTSE 100 DAILY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
ULVR.L	0,05570 %	0,02726 %	RB.L	0,03908 %	0,08324 %
AZN.L	0,10674 %	0,03374 %	AAL.L	0,06254 %	0,15789 %
HSBA.L	0,00425 %	-0,14572 %	LSEG.L	0,24310 %	0,07418 %
RIO.L	0,04205 %	0,23225 %	PRU.L	0,04415 %	0,05254 %
DGE.L	0,04767 %	0,04586 %	GLEN.L	-0,08827 %	0,15850 %
BP.L	-0,02908 %	-0,18687 %	VOD.L	0,07750 %	-0,00503 %
RDSA.L	0,00030 %	-0,10784 %	REL.L	0,09235 %	0,00170 %
GSK.L	0,10013 %	-0,06744 %	BARC.L	0,05940 %	0,01956 %
BATS.L	0,09394 %	0,00313 %	NG.L	0,08274 %	-0,03775 %
BHP.L	0,02245 %	0,17571 %	LLOY.L	0,02889 %	-0,10519 %

OMX HEL 25 DAILY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
NESTE.HE	0,02599 %	0,26064 %	ELISA.HE	0,15215 %	-0,06943 %
KNEBV.HE	0,14136 %	0,12937 %	MOCORP.HE	0,22159 %	0,25551 %
NDA-FI.HE	-0,00216 %	0,00262 %	WRT1V.HE	-0,17413 %	-0,03904 %
SAMPO.HE	-0,00769 %	0,02631 %	ORNBV.HE	0,14072 %	0,04988 %
FORTUM.HE	0,08816 %	0,07634 %	TYRES.HE	-0,08126 %	0,12585 %
NOKIA.HE	-0,21821 %	-0,04638 %	VALMT.HE	-0,01019 %	0,08224 %
UPM.HE	0,08146 %	0,06113 %	HUH1V.HE	0,13604 %	0,06854 %
TELIA1.HE	0,34221 %	0,35194 %	KOJAMO.HE	0,28149 %	0,02194 %
STERV.HE	0,04863 %	0,21745 %	SSABBH.HE	0,32587 %	0,24334 %
KESKOA.HE	0,11209 %	0,17255 %	METSA.HE	-0,08634 %	0,25217 %

NIKKEI 225 DAILY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
7203.T	0,08626 %	0,05785 %	8035.T	0,23494 %	0,24800 %
9984.T	-0,04189 %	0,21492 %	6367.T	0,11617 %	0,22308 %
6758.T	0,16753 %	0,19784 %	4568.T	0,27201 %	0,21577 %
9432.T	0,08877 %	0,04091 %	4502.T	-0,00842 %	0,01424 %
9983.T	0,10043 %	0,23494 %	7267.T	0,00996 %	0,03288 %
6098.T	0,13622 %	0,04638 %	8316.T	0,03204 %	-0,00852 %
9433.T	0,11894 %	0,02173 %	6902.T	0,03297 %	0,19859 %
4519.T	0,14665 %	0,17747 %	6501.T	0,16682 %	0,06482 %
4063.T	0,13578 %	0,20015 %	8001.T	0,13767 %	0,11080 %
8306.T	0,03336 %	-0,04174 %	6954.T	0,04669 %	0,16788 %

From Table 4, it becomes clear that during both periods most stocks had positive daily average returns. This is important to note since it is indicative of the general performance of the markets, as these companies are the largest in their respective indices. This finding explains what the expectation for the two-tailed t-test should be. Since most returns are positive, high beta stocks should experience higher positive returns than low beta stocks.

4.1.2 Weekly rates of return

Table 5: Weekly average rates of return for the 100 stocks traded on the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225 for both the control period and the pandemic period.

S&P 100 WEEKLY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
AAPL	1,19816 %	1,44591 %	WMT	0,51132 %	0,51972 %
MSFT	0,82756 %	0,75374 %	MA	0,66051 %	0,50742 %
AMZN	0,26040 %	1,27255 %	DIS	0,59943 %	1,05153 %
GOOG	0,39444 %	0,68016 %	UNH	0,46764 %	0,49145 %
FB	0,57836 %	0,94495 %	BAC	0,48806 %	0,41887 %
BRK-A	0,24631 %	0,24272 %	PG	0,62187 %	0,33216 %
TSLA	0,88001 %	3,71394 %	NVDA	0,97366 %	1,58693 %
V	0,56131 %	0,40452 %	PYPL	0,23701 %	1,71182 %
JPM	0,72005 %	0,41300 %	HD	0,46300 %	0,40105 %
JNJ	0,18583 %	0,26652 %	XOM	-0,23107 %	-0,17219 %

DAX WEEKLY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
SAP.DE	0,60405 %	0,06175 %	DPW.DE	0,63231 %	1,32114 %
LIN.DE	0,60109 %	0,60904 %	BAYN.DE	0,16554 %	-0,54783 %
SIE.DE	0,46192 %	0,69503 %	BMW.DE	0,08074 %	0,66864 %
VOW3.DE	0,39363 %	0,16479 %	IFX.DE	0,07908 %	1,44573 %
ALV.DE	0,36149 %	0,28351 %	MUV2.DE	0,65968 %	0,17860 %
DAI.DE	-0,00156 %	1,31598 %	HEN.DE	0,08759 %	0,30555 %
DTE.DE	0,13764 %	0,26305 %	VNA.DE	0,35585 %	0,49515 %
BAS.DE	0,09896 %	0,79623 %	CON.DE	-0,47213 %	1,01639 %
MRK.DE	0,33100 %	0,62451 %	DB1.DE	0,56002 %	-0,08060 %
ADS.DE	0,73755 %	0,53876 %	DBK.DE	-0,35177 %	0,64687 %

FTSE 100 WEEKLY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
ULVR.L	0,29350 %	0,07909 %	RB.L	0,20644 %	0,25922 %
AZN.L	0,60127 %	0,04487 %	AAL.L	0,30934 %	0,93564 %
HSBA.L	0,02651 %	-0,61626 %	LSEG.L	1,19481 %	0,42534 %
RIO.L	0,22568 %	1,19943 %	PRU.L	0,20571 %	0,33684 %
DGE.L	0,26981 %	0,15165 %	GLEN.L	-0,41537 %	0,98866 %
BP.L	-0,11502 %	-0,88359 %	VOD.L	0,41361 %	-0,12398 %
RDSA.L	0,02258 %	-0,41511 %	REL.L	0,47190 %	-0,00899 %
GSK.L	0,51343 %	-0,31614 %	BARC.L	0,36135 %	0,26399 %
BATS.L	0,42713 %	-0,14284 %	NG.L	0,42110 %	-0,25210 %
BHP.L	0,13572 %	0,99127 %	LLOY.L	0,14261 %	-0,34264 %

OMX HEL 25 WEEKLY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
NESTE.HE	0,13450 %	1,34415 %	ELISA.HE	0,73971 %	-0,31096 %
KNEBV.HE	0,79182 %	0,70737 %	MOCORP.HE	1,06011 %	1,63327 %
NDA-FI.HE	0,01975 %	0,13007 %	WRT1V.HE	-0,79700 %	0,04190 %
SAMPO.HE	-0,02692 %	0,23041 %	ORNBV.HE	0,69726 %	0,29324 %
FORTUM.HE	0,46635 %	0,46025 %	TYRES.HE	-0,39371 %	0,60353 %
NOKIA.HE	-1,04656 %	-0,01728 %	VALMT.HE	-0,03965 %	0,57400 %
UPM.HE	0,39924 %	0,41786 %	HUH1V.HE	0,67113 %	0,42943 %
TELIA1.HE	1,65761 %	1,69123 %	KOJAMO.HE	1,36112 %	0,10086 %
STERV.HE	0,22443 %	1,17727 %	SSABBH.HE	1,56264 %	1,27552 %
KESKOA.HE	0,53177 %	0,87194 %	METSA.HE	-0,38701 %	1,16492 %

NIKKEI 225 WEEKLY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
7203.T	0,41095 %	0,40914 %	8035.T	1,09881 %	1,31859 %
9984.T	-0,18994 %	1,23430 %	6367.T	0,56448 %	1,17440 %
6758.T	0,80236 %	1,01114 %	4568.T	1,29415 %	1,11799 %
9432.T	0,40858 %	0,23056 %	4502.T	-0,02243 %	0,07674 %
9983.T	0,51357 %	1,22683 %	7267.T	0,05284 %	0,21160 %
6098.T	0,66530 %	0,33943 %	8316.T	0,16602 %	0,16153 %
9433.T	0,56875 %	-0,01887 %	6902.T	0,17399 %	1,14789 %
4519.T	0,69032 %	0,90973 %	6501.T	0,77562 %	0,33644 %
4063.T	0,66850 %	1,03321 %	8001.T	0,64949 %	0,59428 %
8306.T	0,17430 %	-0,02266 %	6954.T	0,26182 %	0,93073 %

Similarly, to Table 4, Table 5 indicates that an even higher number of stocks had positive returns during both periods. As such, the two-tailed t-tests for the weekly returns should provide a positive t-stat to support the CAPM.

4.1.3 Monthly rates of return

Table 6: Monthly average rates of return for the 100 stocks traded on the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225 for both the control period and the pandemic period.

S&P 100 MONTHLY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
AAPL	4,95846 %	8,24515 %	WMT	2,36881 %	2,78780 %
MSFT	3,34372 %	3,90689 %	MA	2,68217 %	4,38326 %
AMZN	0,41092 %	5,70110 %	DIS	3,00613 %	6,98791 %
GOOG	1,45127 %	4,55389 %	UNH	2,06671 %	3,92920 %
FB	2,31214 %	5,48069 %	BAC	2,84577 %	4,18127 %
BRK-A	1,33239 %	2,73187 %	PG	2,24999 %	2,81639 %
TSLA	4,46646 %	21,18993 %	NVDA	3,03577 %	7,60415 %
V	2,10543 %	3,44864 %	PYPL	0,45392 %	9,93933 %
JPM	3,80676 %	4,15408 %	HD	1,66457 %	4,11546 %
JNJ	0,70848 %	2,25490 %	XOM	-1,23208 %	1,60785 %

DAX MONTHLY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
SAP.DE	1,87549 %	0,79385 %	DPW.DE	2,22151 %	6,31658 %
LIN.DE	2,41902 %	3,31092 %	BAYN.DE	3,12108 %	-0,52872 %
SIE.DE	2,16124 %	4,63020 %	BMW.DE	1,25936 %	5,35363 %
VOW3.DE	2,90087 %	4,34799 %	IFX.DE	1,53774 %	9,43331 %
ALV.DE	1,56294 %	3,41827 %	MUV2.DE	2,91845 %	3,57977 %
DAI.DE	0,10419 %	8,91441 %	HEN.DE	0,14775 %	2,31679 %
DTE.DE	0,34219 %	3,63373 %	VNA.DE	0,75240 %	3,87787 %
BAS.DE	0,80336 %	6,02066 %	CON.DE	-1,34064 %	7,80469 %
MRK.DE	0,54346 %	4,77530 %	DB1.DE	2,51689 %	1,41243 %
ADS.DE	3,38486 %	4,32536 %	DBK.DE	-0,34684 %	4,49958 %

FTSE 100 MONTHLY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
ULVR.L	0,14254 %	1,10722 %	RB.L	-0,12701 %	0,97337 %
AZN.L	2,50228 %	0,25432 %	AAL.L	1,16933 %	6,37460 %
HSBA.L	-0,14878 %	-2,01675 %	LSEG.L	5,56244 %	2,49843 %
RIO.L	0,70190 %	5,07363 %	PRU.L	1,53255 %	3,18718 %
DGE.L	0,35967 %	1,36515 %	GLEN.L	-2,62781 %	8,50950 %
BP.L	-1,35601 %	-2,68640 %	VOD.L	1,20876 %	1,12766 %
RDSA.L	-0,33659 %	-0,65497 %	REL.L	1,92388 %	0,67133 %
GSK.L	1,58914 %	-0,94552 %	BARC.L	1,89044 %	4,93099 %
BATS.L	0,70714 %	0,42761 %	NG.L	1,79404 %	-0,42712 %
BHP.L	-0,22850 %	5,42593 %	LLOY.L	0,68736 %	2,31764 %

OMX HEL 25 MONTHLY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
NESTE.HE	0,04981 %	7,61288 %	ELISA.HE	2,73277 %	-2,20067 %
KNEBV.HE	2,88318 %	2,80768 %	MOCORP.HE	4,29775 %	10,04494 %
NDA-FI.HE	1,73840 %	3,81953 %	WRT1V.HE	-3,74787 %	2,88691 %
SAMPO.HE	0,53151 %	4,38671 %	ORNBV.HE	2,83829 %	0,91673 %
FORTUM.HE	2,71797 %	6,06732 %	TYRES.HE	-1,12813 %	3,55272 %
NOKIA.HE	-4,39925 %	1,04174 %	VALMT.HE	-0,30016 %	3,95469 %
UPM.HE	2,44548 %	2,74975 %	HUH1V.HE	2,71935 %	4,63871 %
TELIA1.HE	7,07787 %	7,02200 %	KOJAMO.HE	4,90998 %	0,76125 %
STERV.HE	2,40931 %	6,69751 %	SSABBH.HE	7,94900 %	8,33037 %
KESKOA.HE	2,47286 %	5,84088 %	METSA.HE	-0,98501 %	5,33343 %

NIKKEI 225 MONTHLY					
Tickers	Control period	Pandemic period	Tickers	Control period	Pandemic period
7203.T	2,27513 %	2,44458 %	8035.T	4,83761 %	7,38100 %
9984.T	-1,27606 %	8,48865 %	6367.T	2,08562 %	6,26623 %
6758.T	5,25730 %	5,31021 %	4568.T	4,01895 %	4,13659 %
9432.T	2,18452 %	0,73981 %	4502.T	0,00113 %	1,95690 %
9983.T	2,51575 %	8,24647 %	7267.T	0,70242 %	2,13011 %
6098.T	2,99034 %	4,91610 %	8316.T	0,98822 %	2,89737 %
9433.T	3,90928 %	0,00351 %	6902.T	1,89283 %	6,64676 %
4519.T	3,19935 %	3,23493 %	6501.T	2,97102 %	3,18044 %
4063.T	3,13576 %	5,97376 %	8001.T	3,07334 %	3,47953 %
8306.T	1,30822 %	2,00451 %	6954.T	0,99770 %	6,19367 %

Finally, Table 6 provides a very similar insight into the estimated returns of the individual stocks. Like the daily and weekly frequencies, the monthly data also suggests that nearly all companies had positive returns during both periods. As such, the two-tailed t-tests should present a positive t-stat in order to support the validity of the CAPM.

4.2 Estimated betas for individual stocks

The following section will display the beta estimations for each individual stock in the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225 in both the control period, as well as the pandemic period for daily, weekly, and monthly frequencies. The beta values were calculated by doing a regression analysis of the estimated returns of the stocks and the estimated returns of their respective indices.

4.2.1 Daily beta values

Table 7: Daily beta values for the 100 stocks traded on the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225 for both the control period and the pandemic period.

DAILY BETA VALUES					
Tickers	Control	Pandemic	Tickers	Control	Pandemic
AAPL	1,445769	1,1481704	RB.L	0,663255	0,28355
MSFT	1,278259	1,1609193	AAL.L	1,471339	1,501878
AMZN	1,260962	0,7512933	LSEG.L	1,190621	0,7562832
GOOG	1,286282	0,9854963	PRU.L	1,656874	1,6606145
FB	1,238437	1,0721609	GLEN.L	1,609758	1,49595
BRK-A	0,78949	0,788641	VOD.L	0,864175	0,9842702
TSLA	1,434026	1,2341491	REL.L	0,946626	0,8906733
V	1,040631	1,1067229	BARC.L	1,123857	1,674224
JPM	1,111956	1,2544351	NG.L	0,380152	0,6765672
JNJ	0,511186	0,6795163	LLOY.L	1,056863	1,409102
WMT	0,578016	0,5185544	NESTE.HE	0,597692	0,9949814
MA	1,232166	1,2214301	KNEBV.L	0,463127	0,3195933
DIS	0,816135	1,0460319	NDA-FI.HE	0,708418	1,0200148
UNH	0,673335	1,121365	SAMPO.HE	0,410985	1,0427344

BAC	1,329019	1,3731005	FORTUM.HE	0,341233	0,8106544
PG	0,511646	0,706900	NOKIA.HE	0,492767	0,8718851
NVDA	2,151316	1,3889543	UPM.HE	0,884511	0,6140755
PYPL	1,298982	1,2057104	TELIA1.HE	0,185608	0,4882133
HD	0,838533	1,1265599	STERV.HE	1,110111	0,8502065
XOM	0,935602	1,0533379	KESKOA.HE	0,326435	0,4863505
SAP.DE	1,318259	0,9163189	ELISA.HE	0,103284	0,3749585
LIN.DE	1,018836	0,9291807	MOCORP.HE	1,307489	0,9691924
SIE.DE	1,150775	1,0969191	WRT1V.HE	0,817737	0,9866335
VOW3.DE	1,139801	1,4442606	ORNBV.HE	0,238738	0,2164264
ALV.DE	0,841571	1,1880922	TYRES.HE	0,694574	1,0025839
DAI.DE	1,338676	1,6218446	VALMT.HE	0,684928	0,8108031
DTE.DE	0,387875	0,7318819	HUH1V.HE	0,554954	0,6383028
BAS.DE	1,251534	1,1245915	KOJAMO.HE	0,153491	0,4117353
MRK.DE	0,49013	0,6757981	SSABBH.HE	0,675283	0,9985017
ADS.DE	1,030471	0,9617815	METSA.HE	0,612374	0,3854716
DPW.DE	0,994899	0,914123	7203.T	0,784229	0,8483154
BAYN.DE	1,31065	0,9900502	9984.T	1,281653	1,429032
BMW.DE	1,122141	1,2020583	6758.T	1,036792	0,7668419
IFX.DE	1,707172	1,3090631	9432.T	0,472489	0,311598
MUV2.DE	0,636273	1,1835537	9983.T	0,889846	1,1862117
HEN.DE	0,50435	0,7173958	6098.T	0,882234	1,5053625
VNA.DE	0,037465	0,5579393	9433.T	0,498508	0,524897
CON.DE	1,295139	1,2977085	4519.T	0,552634	0,3961514
DB1.DE	0,52505	0,8178499	4063.T	1,128791	1,2378588
DBK.DE	1,467664	1,3472059	8306.T	0,900495	0,9427685
ULVR.L	0,541447	0,5415415	8035.T	1,268931	1,1363239
AZN.L	0,85667	0,4834625	6367.T	1,13713	0,7972461
HSBA.L	1,004653	0,9539198	4568.T	0,62009	0,7535612
RIO.L	1,276819	0,9905082	4502.T	0,854042	0,7992186
DGE.L	0,634125	0,9312452	7267.T	1,155102	1,2786471
BP.L	1,055181	1,6321404	8316.T	0,770917	0,8913017
RDSA.L	1,029024	1,6413406	6902.T	1,153242	1,0510794
GSK.L	0,800419	0,6382158	6501.T	1,043841	1,180053
BATS.L	1,131622	0,8127832	8001.T	0,617832	0,7857162
BHP.L	1,347800	1,3173171	6954.T	1,341108	1,1790509

Table 7 provides a useful look into the directionality of the beta values. What is notable for the daily beta values is that there are no negative betas. This indicates that high beta stocks should, on the daily frequency, always move in the same direction with the index. For this research, the information provided by the beta table is useful as it states that on a daily level, both during the control period and the pandemic period, the high beta stocks should outperform the low beta stocks, assuming that the CAPM is valid.

4.2.2 Weekly beta values

Table 8: Weekly beta values for the 100 stocks traded on the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225 for both the control period and the pandemic period.

WEEKLY BETA VALUES					
Tickers	Control	Pandemic	Tickers	Control	Pandemic
AAPL	1,444828	1,0797669	RB.L	0,552103	0,2329921
MSFT	1,120037	0,9308021	AAL.L	1,72861	1,5036366
AMZN	1,228665	0,523883	LSEG.L	0,285889	1,0079228
GOOG	0,972562	0,8610029	PRU.L	2,440534	1,9455053
FB	0,949796	1,0653939	GLEN.L	2,253569	1,5508634
BRK-A	0,977259	0,796612	VOD.L	0,413788	1,1976449
TSLA	1,543325	2,0556345	REL.L	0,770669	1,0214258
V	0,895544	1,1038573	BARC.L	1,406149	1,6540749
JPM	1,160709	1,2913491	NG.L	0,351441	0,6364369
JNJ	0,633809	0,6171216	LLOY.L	0,893613	1,4619504
WMT	0,464404	0,2232253	NESTE.HE	0,736904	1,1889007
MA	0,872322	1,4313942	KNEBV.L	0,53758	0,4101801
DIS	0,997166	1,1597338	NDA-FI.HE	2,036962	1,3069159
UNH	0,896537	1,4406907	SAMPO.HE	0,845248	1,3771552
BAC	1,46308	1,3410166	FORTUM.HE	0,717134	1,3614597
PG	0,569636	0,6292867	NOKIA.HE	0,856722	1,2995064
NVDA	2,012524	1,2805579	UPM.HE	1,216215	0,8295991
PYPL	0,995199	1,2135348	TELIA1.HE	0,28376	0,7248001
HD	0,823724	1,4603066	STERV.HE	1,764155	1,0200883
XOM	1,034931	1,2199659	KESKOA.HE	0,304339	0,6192032
SAP.DE	1,030544	0,9907699	ELISA.HE	-0,08848	0,5553011
LIN.DE	1,136776	0,7425743	MOCORP.HE	2,22164	1,266739
SIE.DE	1,271858	0,9959129	WRT1V.HE	1,281557	1,189593

VOW3.DE	1,476736	1,3992855	ORNBV.HE	0,783608	0,4875376
ALV.DE	0,99508	1,2248187	TYRES.HE	1,48212	1,0686561
DAI.DE	1,875257	1,5899365	VALMT.HE	1,358345	0,7543249
DTE.DE	0,364015	0,7943741	HUH1V.HE	0,606634	0,9762578
BAS.DE	1,509179	1,1692415	KOJAMO.HE	-0,10046	0,4270471
MRK.DE	0,399427	0,6285519	SSABBH.HE	1,545679	1,637704
ADS.DE	0,782276	1,2477433	METSA.HE	1,79145	0,5730157
DPW.DE	1,121544	0,6998147	7203.T	1,153551	0,7446673
BAYN.DE	0,976358	0,9068397	9984.T	1,099725	1,5361671
BMW.DE	1,429054	1,2041361	6758.T	0,719731	0,7275756
IFX.DE	1,866895	1,2285879	9432.T	0,223137	0,5295691
MUV2.DE	0,52488	1,2905189	9983.T	1,100049	1,0589876
HEN.DE	0,525621	0,7119076	6098.T	0,493744	1,5997356
VNA.DE	-0,58285	0,6401661	9433.T	0,274422	0,6594733
CON.DE	1,657763	1,3347689	4519.T	-0,03537	0,391606
DB1.DE	0,31475	0,894456	4063.T	1,529461	1,2144554
DBK.DE	1,58603	1,2740662	8306.T	1,171351	1,1322541
ULVR.L	0,127381	0,9283911	8035.T	1,466279	1,2025835
AZN.L	0,823708	0,510894	6367.T	0,803756	0,6982587
HSBA.L	1,212842	0,6177617	4568.T	-0,00576	0,9905245
RIO.L	1,509205	0,4839606	4502.T	0,632045	0,9937807
DGE.L	0,19916	0,6955507	7267.T	1,711286	1,1366121
BP.L	1,164414	1,7422552	8316.T	1,100169	1,0720451
RDSA.L	1,107535	1,6646655	6902.T	1,655711	1,0756881
GSK.L	0,666912	0,5932845	6501.T	1,078519	1,3677662
BATS.L	1,337023	0,6724079	8001.T	0,608553	0,8853485
BHP.L	1,324635	1,0365496	6954.T	1,810497	1,2296216

Unlike the only positive beta values in Table 7, Table 8 does provide a few examples of individual stocks that have negative beta values. However, the number of negative betas is very low, and as such, it can be assumed that most stocks still behave similarly to the market that they are being compared to. Interestingly for this research, those stocks that have negative betas only have them in the control period. Moving into the pandemic period, every individual stock has a positive beta. This indicates that under a time of financial crisis, the individual stocks and markets move more in line with each other. It also means that the two-tailed t-test should provide more uniform results as all average returns should be positive, since the returns for daily, weekly, and monthly frequencies were almost entirely positive.

4.2.3 Monthly beta values

Table 9: Monthly beta values for the 100 stocks traded on the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225 for both the control period and the pandemic period.

MONTHLY BETA VALUES					
Tickers	Control	Pandemic	Tickers	Control	Pandemic
AAPL	1,916057	1,5043163	RB.L	-0,06031	0,2142559
MSFT	1,04091	0,9678674	AAL.L	1,908523	1,3126548
AMZN	1,17981	1,4071227	LSEG.L	0,748911	0,2207153
GOOG	0,623948	0,9133616	PRU.L	2,7706	2,2136312
FB	1,499532	1,4233344	GLEN.L	1,795138	1,8437618
BRK-A	1,207397	0,8930723	VOD.L	0,789363	1,3611113
TSLA	2,906965	3,7964657	REL.L	0,273694	1,5791565
V	0,580319	1,2926198	BARC.L	1,638749	1,7420754
JPM	1,408764	0,7899688	NG.L	0,71876	-0,29673
JNJ	0,991448	0,9814918	LLOY.L	0,8806	1,6422613
WMT	0,493939	0,5978811	NESTE.HE	0,223741	1,2033124
MA	0,448423	1,683509	KNEBV.L	0,300769	0,7474443
DIS	1,172071	1,2782579	NDA-FI.HE	2,133345	1,1464127
UNH	0,167626	0,8526134	SAMPO.HE	0,612716	1,2499754
BAC	2,033316	1,120604	FORTUM.HE	0,374876	1,6764228
PG	0,421451	0,4082032	NOKIA.HE	0,208465	1,7402371
NVDA	3,116713	1,0466031	UPM.HE	1,068395	0,7311493
PYPL	0,612218	1,3853614	TELIA1.HE	-2,43963	1,4237351
HD	0,709594	0,9502223	STERV.HE	1,979208	1,2168594
XOM	1,460258	1,4479496	KESKOA.HE	0,166532	0,1598678
SAP.DE	1,457053	1,8319068	ELISA.HE	-0,25135	0,8488255
LIN.DE	0,575678	0,7231158	MOCORP.HE	4,095169	1,2561309
SIE.DE	1,562328	0,9112386	WRT1V.HE	0,617399	0,4308581
VOW3.DE	1,612895	1,2021084	ORNBV.HE	0,718151	1,4309377
ALV.DE	1,395917	1,4075653	TYRES.HE	1,537359	0,0871969
DAI.DE	2,785217	1,0396607	VALMT.HE	2,495973	0,9264465
DTE.DE	0,261493	1,1279919	HUH1V.HE	0,563767	0,5339051
BAS.DE	2,294825	1,3092426	KOJAMO.HE	0,012915	0,1805164

MRK.DE	0,338225	0,0917467	SSABBH.HE	-2,3607	0,9277134
ADS.DE	-0,03224	0,4512496	METSA.HE	2,415647	0,5442931
DPW.DE	1,594009	0,4658827	7203.T	0,980218	0,6274627
BAYN.DE	0,606598	1,9855269	9984.T	1,086817	-0,211437
BMW.DE	2,286269	1,1039814	6758.T	0,656329	0,126414
IFX.DE	2,256049	1,0647338	9432.T	-0,18816	0,6352344
MUV2.DE	0,910019	1,1489904	9983.T	1,046493	1,3115107
HEN.DE	0,507185	0,2583541	6098.T	0,756173	1,5449166
VNA.DE	-0,8486	0,6026361	9433.T	-0,12520	0,2894662
CON.DE	2,024359	1,1115884	4519.T	0,187029	2,298103
DB1.DE	-0,07728	1,3017219	4063.T	1,733029	1,1497857
DBK.DE	1,518093	0,74399	8306.T	1,045563	1,0383712
ULVR.L	-0,42002	0,2498877	8035.T	1,70101	0,4812577
AZN.L	0,08443	0,379335	6367.T	1,161455	1,018693
HSBA.L	1,640555	0,8875325	4568.T	0,404234	2,2335762
RIO.L	1,555402	0,9101734	4502.T	0,899483	1,6197939
DGE.L	-0,00335	0,7701397	7267.T	1,73929	1,5176761
BP.L	1,167833	2,0572432	8316.T	1,143358	0,9906649
RDSA.L	1,632002	1,8879324	6902.T	1,73584	0,4899213
GSK.L	0,538793	0,9916682	6501.T	0,736296	1,1285066
BATS.L	1,448311	1,5516915	8001.T	0,280627	0,9052516
BHP.L	1,524335	1,3087094	6954.T	1,615765	0,9466972

Finally, Table 9 indicates that the weekly and monthly beta values are relatively similar. While some individual stocks have negative betas in the control period, the general direction of the individual stocks is the same as their respective markets. Furthermore, like the weekly data, the monthly data also further confirms that during the pandemic period, the correlation between the stocks and the markets is stronger, with all the negative betas changing into positive ones.

4.3 Selected stocks with statistically significant high and low beta values

Since this research tests the validity of the CAPM through a comparison between the returns of low beta and high beta stocks, using beta values that are statistically significant adds a higher degree of confidence to the results. As such, out of the 100 individual stocks, only those that had statistically significant betas equal or higher than

1.50 or equal or lower than 0.80, were used in the two-tailed t-tests. To have a better understanding of the selected stocks and of the ratio between high and low betas, the individual stocks that fulfilled the aforementioned criteria are presented in the tables below, with high beta stocks highlighted in yellow.

4.3.1 Selected stocks for the daily frequency

Table 10: The selected stocks from the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225, and their daily average returns and betas for the control period.

Control Period Daily					
Tickers	Return	Beta	Tickers	Return	Beta
BRK-B	0,050195 %	0,789490	KNEBV.HE	0,141357 %	0,46313
JNJ	0,033430 %	0,51119	NDA-FI.HE	-0,002161 %	0,70842
WMT	0,103941 %	0,57802	SAMPO.HE	-0,007687 %	0,41099
UNH	0,092333 %	0,67333	FORTUM.HE	0,088156 %	0,34123
PG	0,121178 %	0,51165	NOKIA.HE	-0,218213 %	0,49277
NVDA	0,189641 %	2,15132	KESKOA.HE	0,112089 %	0,32644
DTE.DE	0,023661 %	0,38788	ORNBV.HE	0,140716 %	0,23874
MRK.DE	0,068657 %	0,49013	TYRES.HE	-0,081263 %	0,69457
IFX.DE	0,015638 %	1,70717	VALMT.HE	-0,010191 %	0,68493
MUV2.DE	0,132009 %	0,63627	HUH1V.HE	0,136045 %	0,55495
HEN.DE	0,014401 %	0,504350	METSA.HE	-0,086342 %	0,61237
DB1.DE	0,114403 %	0,525050	7203.T	0,086261 %	0,78423
ULVR.L	0,055703 %	0,54145	9432.T	0,088773 %	0,47249
DGE.L	0,047671 %	0,63413	9433.T	0,118945 %	0,49851
RB.L	0,039080 %	0,66326	4519.T	0,146649 %	0,55263
PRU.L	0,044147 %	1,65687	4568.T	0,272007 %	0,620090
GLEN.L	-0,088272 %	1,60976	8316.T	0,032042 %	0,77092
NG.L	0,082739 %	0,38015	8001.T	0,137673 %	0,61783
NESTE.HE	0,025985 %	0,59769			

Table 10 clearly shows one of the problems of using daily data. On a daily level the volatility of individual stocks is, on average, so small, that most stocks end up with low beta values. In fact, for the control period, only four stocks had betas higher than 1.50. This means that when doing the two-tailed t-test, the data is heavily skewed towards the returns of the low beta stocks, as they make up such a significant portion of the data set.

Table 11: The selected stocks from the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225, and their daily average returns and betas for the pandemic period.

Pandemic Period Daily					
Tickers	Return	Beta	Tickers	Return	Beta
AMZN	0,252721 %	0,75129	KNEBV.HE	0,129372 %	0,31959
BRK-B	0,028922 %	0,78864	UPM.HE	0,061134 %	0,61408
JNJ	0,055496 %	0,67952	TELIA1.HE	0,351938 %	0,48821
WMT	0,112331 %	0,51855	KESKOA.HE	0,172548 %	0,48635
PG	0,078547 %	0,706900	ELISA.HE	-0,069433 %	0,37496
DAI.DE	0,247758 %	1,62184	ORNBV.HE	0,049883 %	0,21643
DTE.DE	0,045966 %	0,73188	HUH1V.HE	0,068540 %	0,6383
MRK.DE	0,110165 %	0,6758	KOJAMO.HE	0,021937 %	0,41174
HEN.DE	0,038183 %	0,7174	METSA.HE	0,252170 %	0,38547
VNA.DE	0,109883 %	0,55794	6758.T	0,197837 %	0,76684
AZN.L	0,033741 %	0,48346	9432.T	0,040914 %	0,3116
BP.L	-0,186868 %	1,63214	6098.T	0,046380 %	1,50536
RDSA.L	-0,107840 %	1,64134	9433.T	0,021727 %	0,5249
GSK.L	-0,067438 %	0,63822	4519.T	0,177466 %	0,39615
RB.L	0,083244 %	0,28355	6367.T	0,223084 %	0,79725
AAL.L	0,157887 %	1,50188	4568.T	0,215773 %	0,75356
PRU.L	0,052542 %	1,66061	4502.T	0,014236 %	0,79922
BARC.L	0,019561 %	1,67422	8001.T	0,110799 %	0,78572
NG.L	-0,037753 %	0,67657			

Table 11 has the same problem as Table 10. Using daily data means that most individual stocks have a low beta value. While there are seven high beta stocks instead of the four, the data is still heavily skewed towards the returns of the low beta stocks, and as such, the results of the t-test will also be skewed.

4.3.2 Selected stocks for the weekly frequency

Table 12: The selected stocks from the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225, and their weekly average returns and betas for the control period.

Control Period Weekly					
Tickers	Return	Beta	Tickers	Return	Beta
TSLA	0,8800122 %	1,54333	PRU.L	0,2057144 %	2,44053
JNJ	0,1858261 %	0,63381	GLEN.L	-0,415368 %	2,25357
WMT	0,5113172 %	0,4644	REL.L	0,4718967 %	0,77067
PG	0,6218745 %	0,56964	NESTE.HE	0,1344974 %	0,7369
NVDA	0,9736576 %	2,01252	KNEBV.HE	0,7918215 %	0,537580
DAI.DE	-0,001556 %	1,87526	NDA-FI.HE	0,0197462 %	2,03696
DTE.DE	0,1376408 %	0,36402	FORTUM.HE	0,4663535 %	0,71713
BAS.DE	0,0989621 %	1,50918	STERV.HE	0,2244289 %	1,76415
MRK.DE	0,3310030 %	0,39943	MOCORP.HE	1,0601124 %	2,221640
ADS.DE	0,7375538 %	0,78228	ORNBV.HE	0,6972565 %	0,78361
IFX.DE	0,0790772 %	1,8669	HUH1V.HE	0,6711322 %	0,60663
MUV2.DE	0,6596831 %	0,524880	METSA.HE	-0,387008 %	1,791450
HEN.DE	0,0875889 %	0,52562	6758.T	0,8023591 %	0,71973
VNA.DE	0,3558539 %	-0,58285	4063.T	0,6685003 %	1,52946
CON.DE	-0,472125 %	1,65776	4502.T	-0,022429 %	0,63204
DB1.DE	0,5600197 %	0,314750	7267.T	0,0528434 %	1,71129
DBK.DE	-0,351774 %	1,586030	6902.T	0,1739912 %	1,65571
RIO.L	0,2256828 %	1,5092	8001.T	0,6494940 %	0,60855
GSK.L	0,5134302 %	0,66691	6954.T	0,2618214 %	1,8105
AAL.L	0,3093447 %	1,728610			

Table 12 gives a much better ratio between high and low beta stocks. The high beta stocks make up around 48.7% of the data set, and as such, the results of the two-tailed t-test should provide a meaningful and statistically significant result.

Table 13: The selected stocks from the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225, and their weekly average returns and betas for the pandemic period.

Pandemic Period Weekly					
Tickers	Return	Beta	Tickers	Return	Beta
AMZN	1,272554 %	0,52388	PRU.L	0,336839 %	1,94551
BRK-B	0,242716 %	0,79661	GLEN.L	0,988657 %	1,55086
TSLA	3,713939 %	2,05563	BARC.L	0,263986 %	1,65407
JNJ	0,266523 %	0,61712	NG.L	-0,252104 %	0,63644
PG	0,332163 %	0,62929	KNEBV.HE	0,707367 %	0,410180
LIN.DE	0,609043 %	0,74257	TELIA1.HE	1,691231 %	0,724800
DAI.DE	1,315976 %	1,58994	KESKOA.HE	0,871944 %	0,6192
DTE.DE	0,263047 %	0,79437	ELISA.HE	-0,310955 %	0,5553
MRK.DE	0,624513 %	0,62855	ORNBV.HE	0,293237 %	0,48754
DPW.DE	1,321136 %	0,69981	VALMT.HE	0,573998 %	0,75432
HEN.DE	0,305547 %	0,71191	KOJAMO.HE	0,100858 %	0,42705
VNA.DE	0,495155 %	0,64017	SSABBH.HE	1,275518 %	1,6377
AZN.L	0,044866 %	0,51089	METSA.HE	1,164920 %	0,57302
HSBA.L	-0,616256 %	0,61776	7203.T	0,409136 %	0,74467
RIO.L	1,199434 %	0,48396	9984.T	1,234299 %	1,53617
DGE.L	0,151654 %	0,69555	6758.T	1,011136 %	0,72758
BP.L	-0,883593 %	1,74226	9432.T	0,230558 %	0,52957
RDSA.L	-0,415113 %	1,66467	6098.T	0,339429 %	1,59974
GSK.L	-0,316142 %	0,59328	9433.T	-0,018866 %	0,65947
BATS.L	-0,142836 %	0,67241	4519.T	0,909733 %	0,39161
AAL.L	0,935640 %	1,50364	6367.T	1,174396 %	0,69826

Table 13 also has a better ratio of high beta stocks. However, the pandemic period did not have as many high beta stocks as the control period did. In fact, only around 26% of the data set consists of stocks with betas higher than 1.50. While this set of data should provide better results than the ones with daily frequencies, the data is skewed towards the returns of low beta stocks, which will affect the results of the two-tailed t-test.

4.3.3 Selected stocks for the monthly frequency

Table 14: The selected stocks from the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225, and their monthly average returns and betas for the control period.

Control Period Monthly					
Tickers	Return	Beta	Tickers	Return	Beta
AAPL	4,958459 %	1,91606	BHP.L	-0,22850 %	1,52433
BAC	2,845768 %	2,03332	PRU.L	1,53255 %	2,770600
NVDA	3,035775 %	3,11671	GLEN.L	-2,62781 %	1,79514
SIE.DE	2,161240 %	1,56233	NDA-FI.HE	1,73840 %	2,13335
VOW3.DE	2,900866 %	1,6129	STERV.HE	2,40931 %	1,97921
DAI.DE	0,104192 %	2,78522	MOCORP.HE	4,29775 %	4,09517
BAS.DE	0,803356 %	2,29482	TYRES.HE	-1,12813 %	1,53736
DPW.DE	2,221509 %	1,59401	VALMT.HE	-0,30016 %	2,49597
BMW.DE	1,259364 %	2,28627	METSA.HE	-0,98501 %	2,41565
IFX.DE	1,537739 %	2,25605	6758.T	5,25730 %	0,65633
VNA.DE	0,752398 %	-0,84860	4519.T	3,19935 %	0,18703
CON.DE	-1,340636 %	2,02436	4063.T	3,13576 %	1,73303
HSBA.L	-0,148780 %	1,64055	8035.T	4,83761 %	1,701010
RIO.L	0,701899 %	1,5554	7267.T	0,70242 %	1,739290
RDSA.L	-0,336588 %	1,632	6902.T	1,89283 %	1,735840
GSK.L	1,589136 %	0,53879	6954.T	0,99770 %	1,61577

While the daily frequency data was heavily skewed towards low betas, the opposite happens with monthly data. In fact, the data set is even more concentrated towards one side, high beta, then the daily data. Out of the 32 companies only three had a low beta during the control period with a monthly frequency. This means that the results of the two-tailed t-test will be significantly skewed towards the returns of the high beta stocks.

Table 15: The selected stocks from the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225, and their monthly average returns and betas for the pandemic period.

Pandemic Period Monthly					
Tickers	Return	Beta	Tickers	Return	Beta
AAPL	8,245146 %	1,50432	GLEN.L	8,509501 %	1,84376
TSLA	21,189932 %	3,79647	REL.L	0,671327 %	1,57916
MA	4,383260 %	1,68351	BARC.L	4,930989 %	1,74208
SAP.DE	0,793845 %	1,83191	LLOY.L	2,317644 %	1,64226
LIN.DE	3,310916 %	0,72312	FORTUM.HE	6,067323 %	1,67642
BAYN.DE	-0,528724 %	1,98553	NOKIA.HE	1,041737 %	1,74024
BP.L	-2,686400 %	2,05724	6098.T	4,916104 %	1,54492
RDSA.L	-0,654971 %	1,88793	4568.T	4,136589 %	2,23358
BATS.L	0,427611 %	1,55169	4502.T	1,956899 %	1,61979
PRU.L	3,187185 %	2,21363	7267.T	2,130114 %	1,51768

Similarly, to Table 14, Table 15 also has a heavily skewed set of data. Indeed, out of the six sets of selected stocks, the monthly data for the pandemic period has the worst ratio between high and low beta stocks. Out of the 20 stocks, only one has a low beta. These results provide a clear signal that weekly data is the most even when it comes to the ratio of low beta and high beta stocks.

4.4 Examination of the statistical difference between high and low beta stocks

After calculating the estimated returns for the individual stocks and the selected indices for the daily, weekly, and monthly frequencies, and using those estimations to calculate the estimated betas using regression analysis, the author was able to determine stocks that had statistically significant betas of 1.50 or higher, or 0.80 or lower. The selected companies and their daily, weekly, and monthly estimated returns were divided into groups of high and low beta stocks. These two groups were compared by running a two-tailed t-test assuming unequal variances on the returns in order to determine if there is a significant difference between the two groups. Assuming that the CAPM is valid, the returns of high beta stocks and low beta stocks should be significantly different.

The following table provides the results of the six tests that were done, including the t-stat, as well as the t critical one tail.

Table 16: Results of the two-tailed t-tests

	Control Period		Pandemic Period	
Daily	T-stat	-0,393919842	T-stat	-1,080914818
	One tail critical	2,353363435	One tail critical	1,894578605
Weekly	T-stat	-2,369929085	T-stat	0,954325488
	One tail critical	1,782287556	One tail critical	1,782287556
Monthly	T-stat	-0,804288788	T-stat	0,361225939
	One tail critical	2,91998558	One tail critical	#NUM!

Out of the six tests, only one provided statistically significant results at a 5% confidence level. The two-tailed t-test examining the weekly frequency data during the control period provided results where the t-stat had a higher absolute value than the one tail critical, making it statistically significant. However, notably, the t-stat is negative. The other control period tests were not statistically significant; however, they share the same negative t-stat characteristic with the weekly data.

The weekly data during the pandemic period, however, had a positive t-stat. Nonetheless, as the data set did not have an even number of high and low beta stocks, the result is statistically insignificant at a 5% confidence level. Furthermore, due to the highly imbalanced ratio of high and low beta stocks for the monthly frequency during the pandemic, no usable data was gained.

As such, the author is unable to reject the null hypothesis of hypotheses H_1, H_2, H_3, H_4, H_5, and H_6.

4.5 Discussion

This research paper investigated the validity of the Capital Asset Pricing Model under rare market conditions, in this case, the Covid-19 pandemic. This was achieved by comparing two periods, the control period between March 1st, 2019 and December 31st, 2019, and the pandemic period between March 1st, 2020 and December 31st,

2020. Within both these periods the selected stocks from the S&P 100, DAX, FTSE 100, OMX Helsinki 25, and Nikkei 225 were divided into high beta and low beta stocks. In order to determine the validity of the CAPM, the two groups of stocks were subjected to a two-tailed t-test assuming unequal variances. Based on the results of those tests, as well as the results of previous studies, the author is able to explore the implications of the findings. The following part aims to discuss those implications.

Most notably, the research has been unable to reject all six null hypotheses at the 5% level of significance. As a conclusion, the research can claim that there is little proof of the validity of the CAPM in either the control period or the pandemic period. While the weekly data for the control period does provide evidence for a significant difference in the returns of high and low beta stocks, the negative t-stat value, and a higher mean return for low beta stocks, signals that low beta stocks outperformed high beta stocks. Furthermore, the research can also claim that there is no significant difference between the returns of high and low beta stocks in the pandemic period, and that, within the control period, the negative t-stats could be explained by the higher mean returns that the low beta stocks experienced. This means that under normal bullish markets, the CAPM is not valid. This result further supports the findings of previous studies, such as Fama and French (1992), Banz (1981) and Dajcman, Festic and Kavkler (2013), into the validity of the CAPM in both developed and developing markets. In addition, the findings support those of Fatnassi and Hasnaoui (2014) and Curran and Velic (2020). Both of these studies found evidence for an inverse relationship between risk and return during periods of high volatility caused by a financial market crisis.

However, it should also be noted that at the weekly frequency during the pandemic period, the results suggested that there might be some support for the CAPM. While the findings were statistically insignificant, there was a difference between the returns of high and low beta stocks that suggested that high beta stocks might experience significantly higher returns during unusual market conditions, such as the ones presented by the Covid-19 pandemic. Since the mean return of high beta stocks was higher than that of low beta stocks, and the t-stat was positive, a larger data set might yield statistically significant results that support the validity of the CAPM during the Covid-19 pandemic.

Nevertheless, the findings and results of this study are affected by many factors. Such as the selection of markets, selection of stocks, and the selected time periods. Changing any of the factors could lead to different results and an increase in sample size could lead into more statistically significant results. As such, these findings stand true only when using the same processes and the same data.

5. CONCLUSIONS

This final chapter of the thesis will conclude the research with the main findings. It will also present the implications for international business, as well as discuss the limitations of the study and provide suggestions for further research into the topic.

5.1 Main findings

This thesis is unable to reject the six null hypotheses and finds that the Capital Asset Pricing Model is not valid during normal market conditions, nor during extreme market conditions such as the ones presented by the Covid-19 pandemic, by testing for a significant difference between the returns of high beta and low beta stocks. The six null hypotheses could not be rejected at a 5% level of significance. Therefore, the research concludes by stating that the CAPM is not valid in the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225 in the periods between March 1st, 2019 and December 31st, 2019, and March 1st, 2020 and December 31st, 2020.

5.2 Implications for International Business

Investing overseas has become more and more common. Foreign investments can provide higher returns while also acting as geographical diversification. As such, it is important for professional, and retail investors alike, to be aware of the validity of financial asset pricing models, such as the CAPM. These models provide a means of evaluating companies and estimating returns by simplifying the process into a single formula. Especially in the case of the CAPM, which has gained significant popularity due to its simplicity, it is important that investors are aware of the validity of such a model. Since overseas investing has increased, extending the testing of the validity of these models into foreign markets is becoming increasingly important. As market conditions change and the companies in them evolve, it remains essential that the validity of models such as the CAPM is regularly tested both for domestic markets, as well as foreign ones.

5.3 Limitations and suggestions for further research

In order to ensure that the reader fully understands the significance and impact of the results presented in this thesis, the following section will be dedicated to addressing the limitations of the research. Furthermore, a section for suggestions for future research will be presented in order to help achieve more significant results in the upcoming studies into the topic.

The most notable limitation is the number of stocks in the sample. 100 stocks were selected in total, with only 20 selected from each index and market. Future research could increase the sample size into 480 by including all stocks from the selected indices. Furthermore, the sample size could be increased to 991 by changing the S&P 100 to the S&P 500 and the OMX Helsinki 25 to the OMX Helsinki PI. The sample size could also be increased by including a larger selection of indices. In regard to the methodology when selecting data, the research used only stocks that had statistically significant betas of 1.50 or higher, or 0.80 or lower. With a larger sample size, the number of stocks that fit the criteria would be higher and thus the two-tailed t-test would likely produce more balanced and significant results. Furthermore, the scope of the time periods could be extended in the future. This study used the same time period in both the control and pandemic period in order to reduce the effect of market anomalies that are based on time of year. However, as the pandemic extends further into the future, both the control period and the pandemic period could be extended. Because of the current limitation to the length of data available from the pandemic, the study fails to represent a broader view of the market in the long run. Accordingly, future studies into the topic should attempt to use longer time periods where possible.

Another limitation of the study is its narrow focus. The research examined only the difference in returns between high and low beta stocks, and the significance of it. While the CAPM does assume that there should be a significant difference between the returns of high and low beta stocks, in order to compensate for the higher degree of risk that high beta stocks carry, there are other aspects of the CAPM that could be examined. Future studies could expand on the findings of this study and examine other aspects of the model in order to reach more conclusive results.

Finally, a significant limitation for this study is its scope. Due to the time limitations, a larger selection of stocks and indices, as well as a more comprehensive test of all the aspects of the CAPM, was unobtainable. Expanding the sample size, the time periods studied, as well as the number of tests done, would have a meaningful impact on the results. As such, future research into the topic should, if possible, spend more time gathering a larger set of data. Furthermore, future researchers can also use a wider variety of statistical tools and methods, in order to gain a more comprehensive and meaningful set of results.

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APPENDICES

Appendix 1: Testing the relationship between daily returns of high and low beta stocks.

a. Control period: March 1st, 2019 – December 31st, 2019.

t-Test: Two-Sample Assuming Unequal Variances		
	HIGH BETA	*LOW BETA*
Mean	0,00040289	0,00063644
Variance	1,3152E-06	7,4942E-07
Observations	4	33
Hypothesized Mean Difference	0	
df	3	
t Stat	-0,39391984	
P(T<=t) one-tail	0,35998487	
t Critical one-tail	2,35336343	
P(T<=t) two-tail	0,71996973	
t Critical two-tail	3,18244631	

b. Pandemic period: March 1st, 2020 – December 31st, 2020.

t-Test: Two-Sample Assuming Unequal Variances		
	HIGH BETA	*LOW BETA*
Mean	0,00032774	0,00096131
Variance	2,1773E-06	9,7561E-07
Observations	7	30
Hypothesized Mean Difference	0	
df	7	
t Stat	-1,08091482	
P(T<=t) one-tail	0,15778095	
t Critical one-tail	1,89457861	
P(T<=t) two-tail	0,31556189	
t Critical two-tail	2,36462425	

Appendix 2: Testing the relationship between weekly returns of high and low beta stocks.

a. Control period: March 1st, 2019 – December 31st, 2019.

t-Test: Two-Sample Assuming Unequal Variances		
	HIGH BETA	*LOW BETA*
Mean	0,00189793	0,00468209
Variance	2,0195E-05	6,3446E-06
Observations	19	20
Hypothesized Mean Difference	0	
df	28	
t Stat	-2,36992909	
P(T<=t) one-tail	0,0124587	
t Critical one-tail	1,70113093	
P(T<=t) two-tail	0,0249174	
t Critical two-tail	2,04840714	

b. Pandemic period: March 1st, 2020 – December 31st, 2020.

t-Test: Two-Sample Assuming Unequal Variances		
	HIGH BETA	*LOW BETA*
Mean	0,0082778	0,00471281
Variance	0,00014242	3,1221E-05
Observations	11	31
Hypothesized Mean Difference	0	
df	12	
t Stat	0,95432549	
P(T<=t) one-tail	0,17937426	
t Critical one-tail	1,78228756	
P(T<=t) two-tail	0,35874851	
t Critical two-tail	2,17881283	

Appendix 3: Testing the relationship between weekly returns of high and low beta stocks.

a. Control period: March 1st, 2019 – December 31st, 2019.

t-Test: Two-Sample Assuming Unequal Variances		
	HIGH BETA	*LOW BETA*
Mean	0,01385456	0,02532945
Variance	0,00035274	0,00057416
Observations	29	3
Hypothesized Mean Difference	0	
df	2	
t Stat	-0,80428879	
P(T<=t) one-tail	0,25281913	
t Critical one-tail	2,91998558	
P(T<=t) two-tail	0,50563826	
t Critical two-tail	4,30265273	

b. Pandemic period: March 1st, 2020 – December 31st, 2020.

t-Test: Two-Sample Assuming Unequal Variances		
	HIGH BETA	*LOW BETA*
Mean	0,0373869	0,03310916
Variance	0,00266455	#DIV/0!
Observations	19	1
Hypothesized Mean Difference	0	
df	65535	
t Stat	0,36122594	
P(T<=t) one-tail	#NUM!	
t Critical one-tail	#NUM!	
P(T<=t) two-tail	#NUM!	
t Critical two-tail	#NUM!	